In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
df=pd.read_csv("laptop_data.csv")
```

In [3]:

```
#reading top 5 values from a data.
df.head()
```

Out[3]:

	Unnamed: 0	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gp
0	0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iri Plu Graphic 64
1	1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HI Graphic 600
2	2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HI Graphic 62
3	3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMI Radeo Pro 45
4	4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iri Plu Graphic 65

this is the dataset about laptop details.

In [4]:

```
df.shape
```

Out[4]:

```
(1303, 12)
```

dataset is contains 1303 rows with 12 columns.

In [5]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 12 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Unnamed: 0        1303 non-null   int64  
 1   Company           1303 non-null   object 
 2   TypeName          1303 non-null   object 
 3   Inches            1303 non-null   float64
 4   ScreenResolution  1303 non-null   object 
 5   Cpu               1303 non-null   object 
 6   Ram               1303 non-null   object 
 7   Memory            1303 non-null   object 
 8   Gpu               1303 non-null   object 
 9   OpSys             1303 non-null   object 
 10  Weight            1303 non-null   object 
 11  Price             1303 non-null   float64
dtypes: float64(2), int64(1), object(9)
memory usage: 122.3+ KB
```

In [6]:

```
df.duplicated().sum()
```

Out[6]:

```
0
```

in dataset there is no rows which are identically same.

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
Unnamed: 0          0
Company             0
TypeName            0
Inches              0
ScreenResolution    0
Cpu                 0
Ram                 0
Memory              0
Gpu                 0
OpSys               0
Weight              0
Price               0
dtype: int64
```

dataset contains 0 null value.

In [8]:

```
#deleting unwanted columns.
df.drop(columns=["Unnamed: 0"],inplace=True)
```

In [9]:

```
df.head()
```

Out[9]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys
0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8GB	128GB SSD	Intel Iris Plus Graphics 640	macOS
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8GB	128GB Flash Storage	Intel HD Graphics 6000	macOS
2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8GB	256GB SSD	Intel HD Graphics 620	No OS
3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16GB	512GB SSD	AMD Radeon Pro 455	macOS
4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8GB	256GB SSD	Intel Iris Plus Graphics 650	macOS

"Unnamed: 0" dosent make any sense in dataset hence unwanted column is deleted.

In [10]:

```
df["Ram"]=df["Ram"].str.replace("GB","")
df["Weight"]=df["Weight"].str.replace("kg","")
```

In [11]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Company           1303 non-null   object 
 1   TypeName          1303 non-null   object 
 2   Inches            1303 non-null   float64
 3   ScreenResolution  1303 non-null   object 
 4   Cpu               1303 non-null   object 
 5   Ram               1303 non-null   object 
 6   Memory            1303 non-null   object 
 7   Gpu               1303 non-null   object 
 8   OpSys             1303 non-null   object 
 9   Weight            1303 non-null   object 
 10  Price             1303 non-null   float64
dtypes: float64(2), object(9)
memory usage: 112.1+ KB
```

still dtype of "Weight" and "Ram" is in object.

converting dtype

In [12]:

```
df["Ram"]=df["Ram"].astype("int32")
df["Weight"]=df["Weight"].astype("float32")
```

In [13]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 11 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Company           1303 non-null   object 
 1   TypeName          1303 non-null   object 
 2   Inches            1303 non-null   float64
 3   ScreenResolution  1303 non-null   object 
 4   Cpu               1303 non-null   object 
 5   Ram               1303 non-null   int32  
 6   Memory            1303 non-null   object 
 7   Gpu               1303 non-null   object 
 8   OpSys             1303 non-null   object 
 9   Weight            1303 non-null   float32
 10  Price             1303 non-null   float64
dtypes: float32(1), float64(2), int32(1), object(7)
memory usage: 101.9+ KB
```

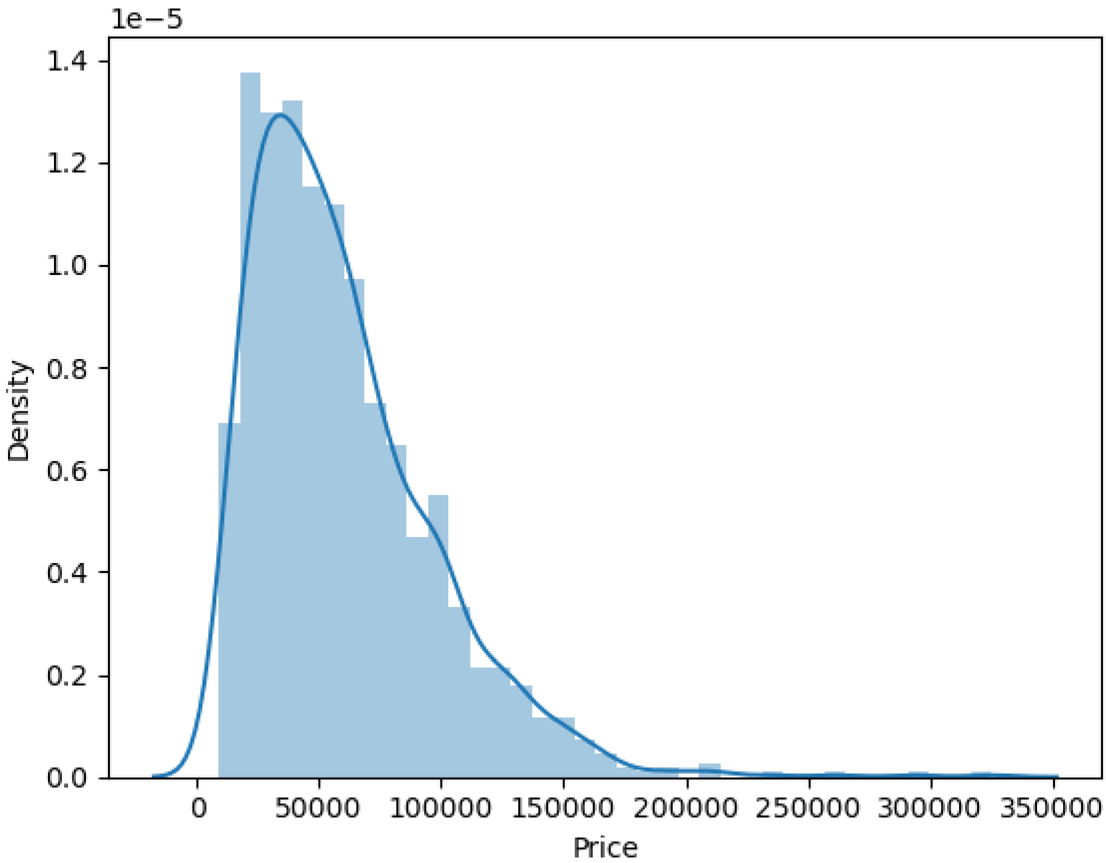
EDA

In [14]:

```
sns.distplot(df["Price"])
```

Out[14]:

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```



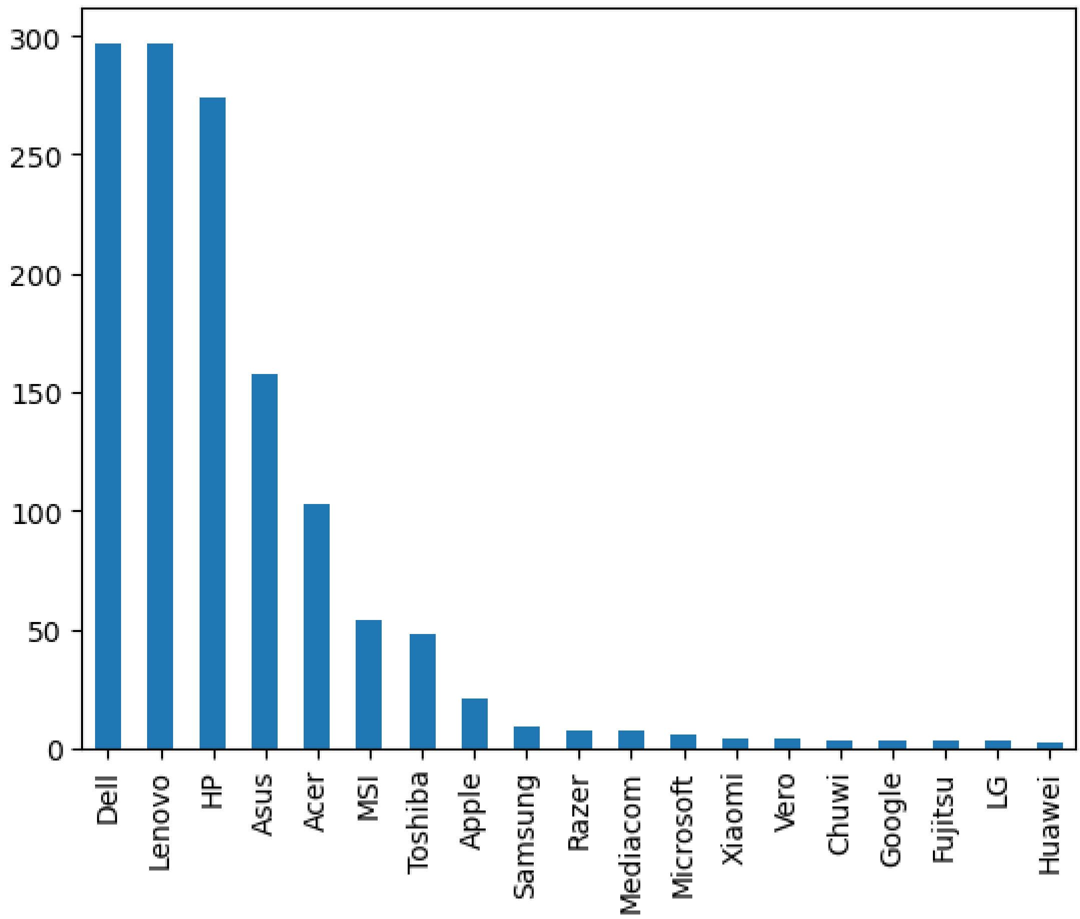
distribution is slightly skewed on right.

In [15]:

```
df["Company"].value_counts().plot(kind="bar")
```

Out[15]:

<AxesSubplot:>

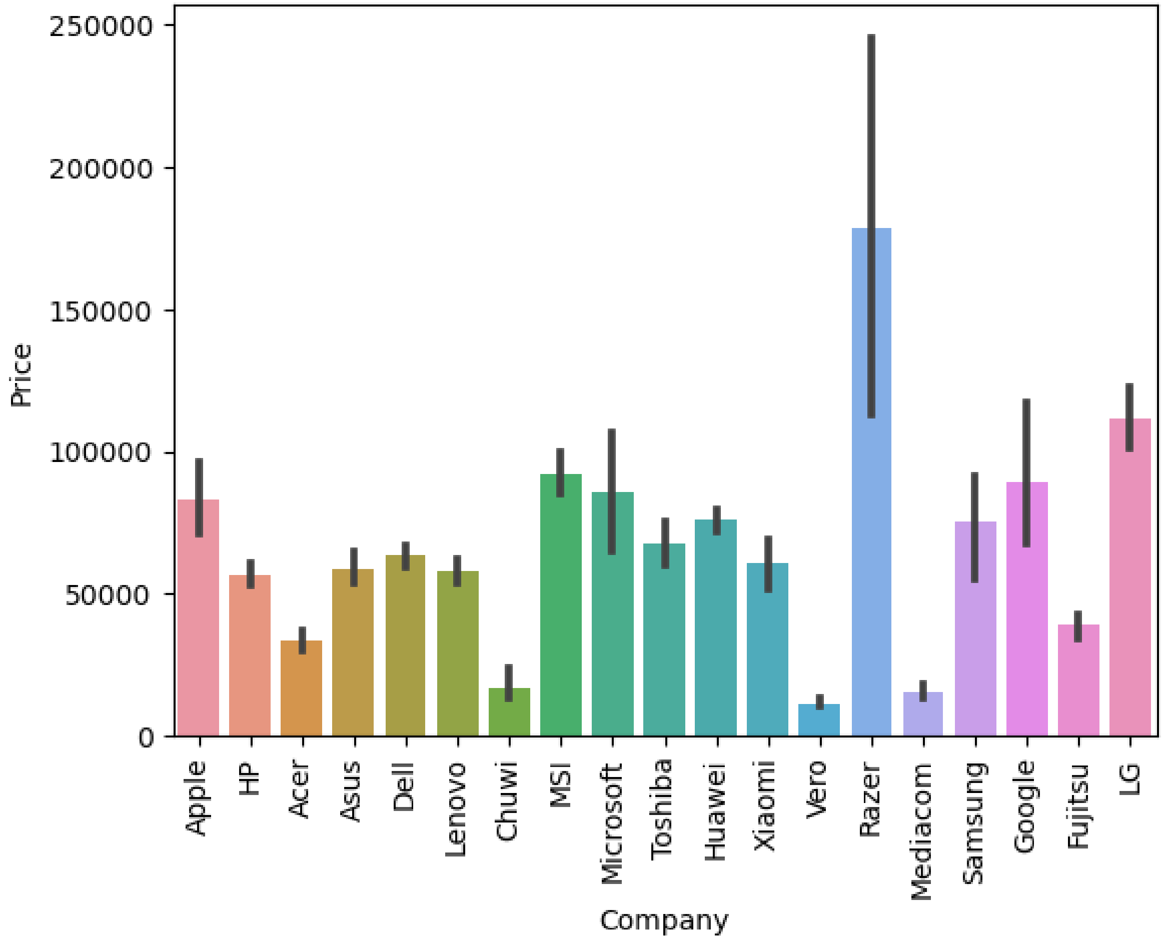


dell,lenevo and hp are having higher number of laptops.

LG and Huawei contains the less number of laptops.

In [16]:

```
sns.barplot(x=df["Company"],y=df["Price"])
plt.xticks(rotation="vertical")
plt.show()
```



Razer company having higher price range above 150000rs hence in indian market it has lower distribution.

there is high number of companies which are lies between 40,000rs to 100000rs which are one of leading distributers.

chuwi,vero are cheep distributer companies.

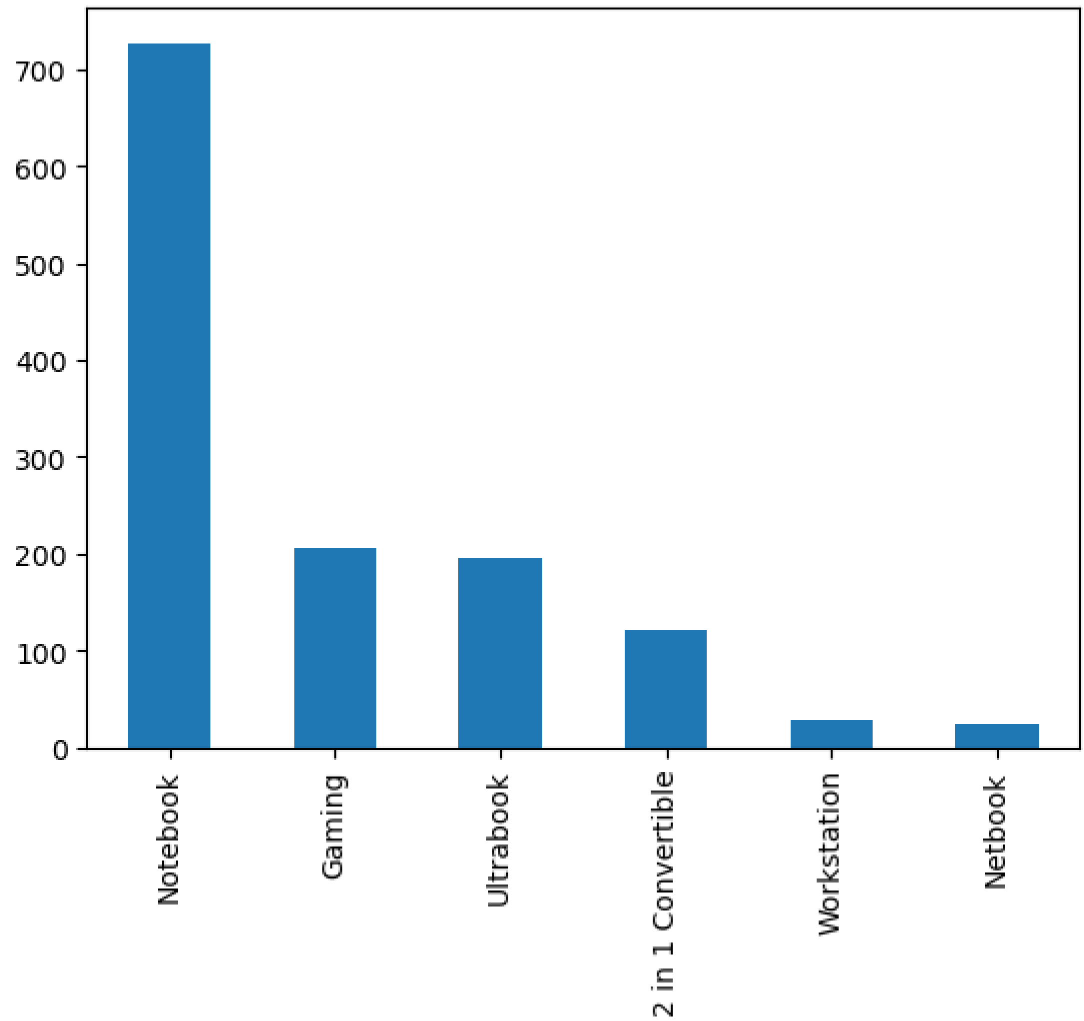
we could say that price range varies according company to company.

In [17]:

```
df["TypeName"].value_counts().plot(kind="bar")
```

Out[17]:

```
<AxesSubplot:>
```

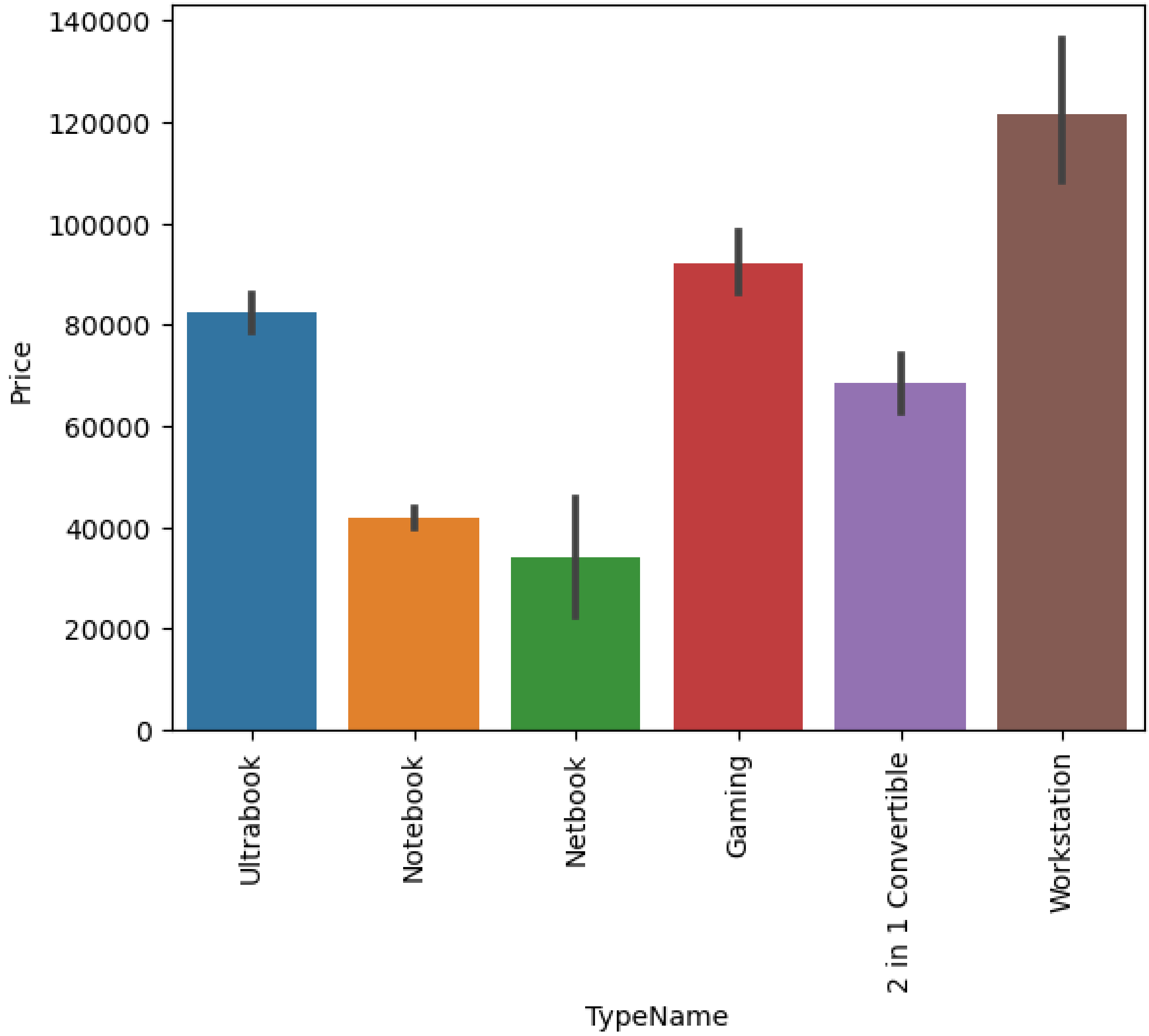


netbook type laptop is less sellable cause its specifiacation.

notebook type laptop is highest sellable.

In [18]:

```
sns.barplot(x=df["TypeName"],y=df["Price"])
plt.xticks(rotation="vertical")
plt.show()
```



workstation and ultrabooktype type laptops are more expensive and thats why in indian market they have less acceptance.

gaming and ultrabook is have a range of higher middle class but cause of its specificatons is have quite of good acceptance.

notebook type laptops provides customer satisfied range with good functionlaties and specifications thats why they are one of best sellers.

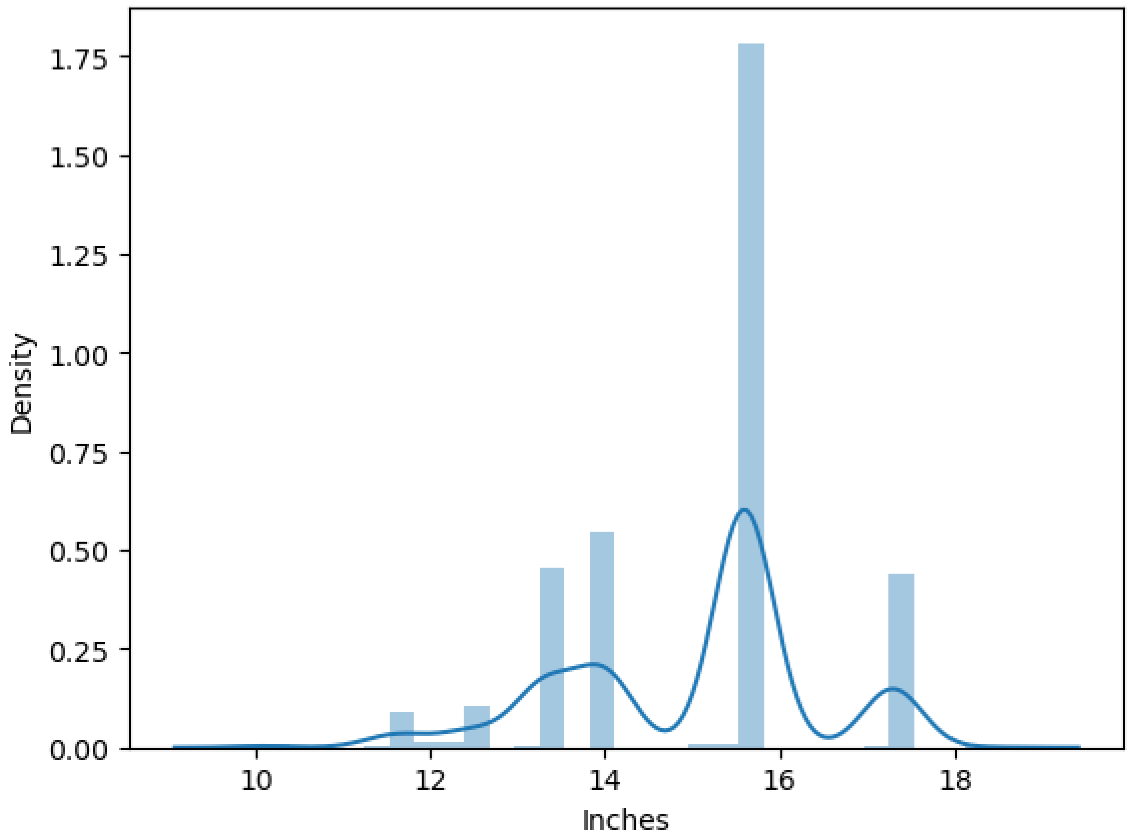
hence here we can say that type of laptop varies type of a price.

In [19]:

```
sns.distplot(df["Inches"])
```

Out[19]:

```
<AxesSubplot:xlabel='Inches', ylabel='Density'>
```

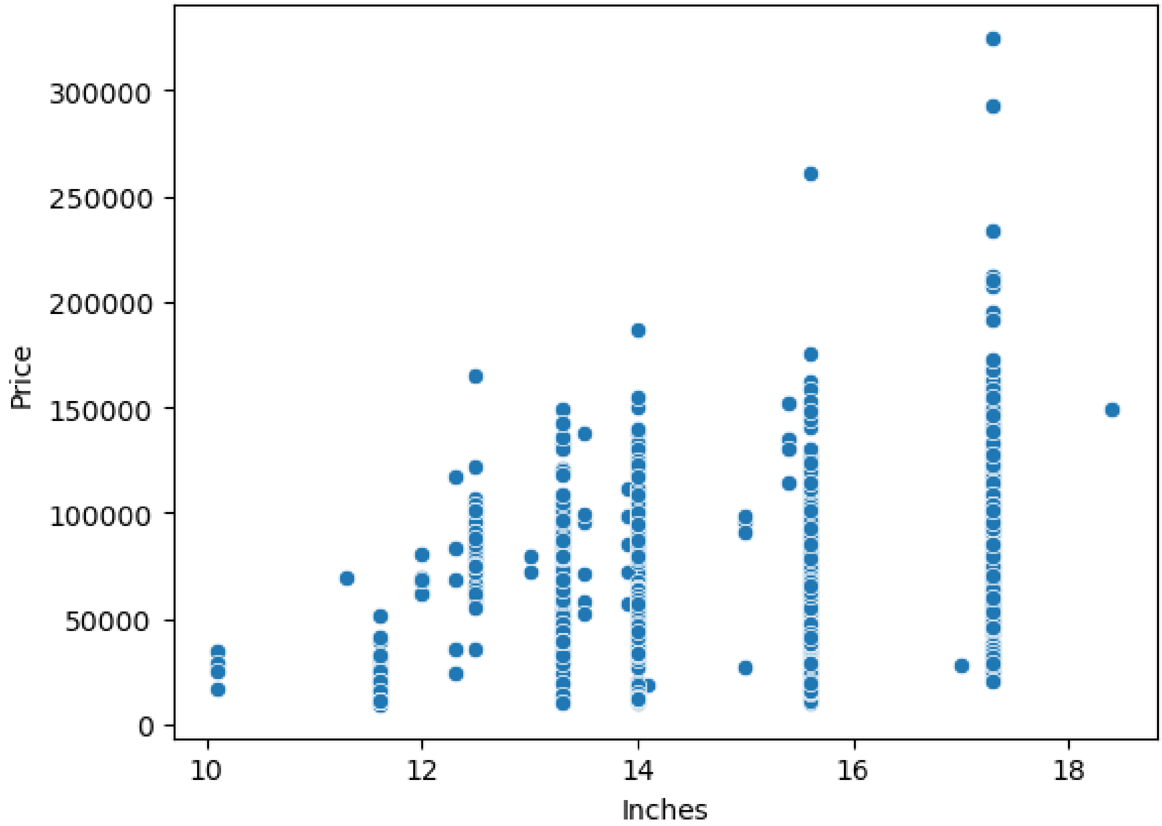


In [20]:

```
sns.scatterplot(x=df["Inches"],y=df["Price"])
```

Out[20]:

```
<AxesSubplot:xlabel='Inches', ylabel='Price'>
```



impact of size on price is not to much dependable but its slightly

varies when have big diffrence.

we can see this price diffrence between 10 inches laptop and 16 or 18 inches laptop.

In [21]:

```
df["ScreenResolution"].value_counts()
```

Out[21]:

```
Full HD 1920x1080                                507
1366x768                                         281
IPS Panel Full HD 1920x1080                      230
IPS Panel Full HD / Touchscreen 1920x1080         53
Full HD / Touchscreen 1920x1080                   47
1600x900                                          23
Touchscreen 1366x768                              16
Quad HD+ / Touchscreen 3200x1800                  15
IPS Panel 4K Ultra HD 3840x2160                   12
IPS Panel 4K Ultra HD / Touchscreen 3840x2160     11
4K Ultra HD / Touchscreen 3840x2160               10
4K Ultra HD 3840x2160                              7
Touchscreen 2560x1440                              7
IPS Panel 1366x768                                 7
IPS Panel Quad HD+ / Touchscreen 3200x1800         6
IPS Panel Retina Display 2560x1600                 6
IPS Panel Retina Display 2304x1440                 6
Touchscreen 2256x1504                              6
IPS Panel Touchscreen 2560x1440                    5
IPS Panel Retina Display 2880x1800                 4
IPS Panel Touchscreen 1920x1200                    4
1440x900                                           4
IPS Panel 2560x1440                                4
IPS Panel Quad HD+ 2560x1440                       3
Quad HD+ 3200x1800                                 3
1920x1080                                          3
Touchscreen 2400x1600                              3
2560x1440                                          3
IPS Panel Touchscreen 1366x768                     3
IPS Panel Touchscreen / 4K Ultra HD 3840x2160      2
IPS Panel Full HD 2160x1440                        2
IPS Panel Quad HD+ 3200x1800                       2
IPS Panel Retina Display 2736x1824                 1
IPS Panel Full HD 1920x1200                        1
IPS Panel Full HD 2560x1440                        1
IPS Panel Full HD 1366x768                         1
Touchscreen / Full HD 1920x1080                    1
Touchscreen / Quad HD+ 3200x1800                   1
Touchscreen / 4K Ultra HD 3840x2160                1
IPS Panel Touchscreen 2400x1600                    1
Name: ScreenResolution, dtype: int64
```

this kind of very mixed information of a column so we have to do some feature engineering over here.

In [22]:

```
df["Touchscreen"]=df["ScreenResolution"].apply(lambda x:1 if "Touchscreen" in x else 0)
```

In [23]:

```
df.sample(5)
```

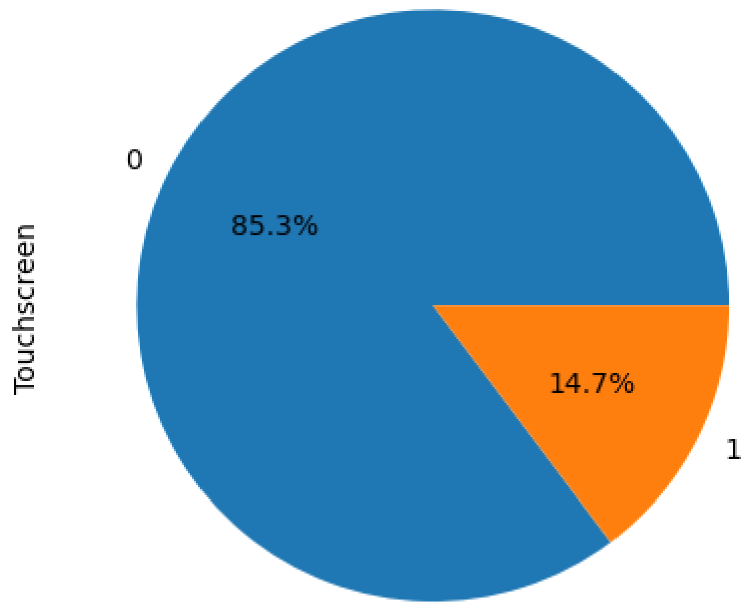
Out[23]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpS
167	Dell	Gaming	15.6	Full HD 1920x1080	Intel Core i7 7700HQ 2.8GHz	8	128GB SSD + 1TB HDD	Nvidia GeForce GTX 1050	Windc
372	Asus	Gaming	17.3	IPS Panel Full HD 1920x1080	AMD Ryzen 1700 3GHz	16	256GB SSD + 1TB HDD	AMD Radeon RX 580	Windc
1049	Asus	Netbook	11.6	1366x768	Intel Celeron Dual Core N3060 1.6GHz	4	16GB Flash Storage	Intel HD Graphics 400	Chro
1220	Lenovo	Notebook	15.6	IPS Panel Full HD 1920x1080	Intel Core i7 6600U 2.6GHz	8	256GB SSD	Intel HD Graphics 520	Windc
887	Asus	Gaming	17.3	Full HD 1920x1080	Intel Core i5 7300HQ 2.5GHz	12	128GB SSD + 1TB HDD	Nvidia GeForce GTX 1050	Windc

here new columm "Touchscreen" is added to the dataset and 1 denotes "yes" and 0 "No".

In [24]:

```
df["Touchscreen"].value_counts().plot(kind="pie",autopct="%0.1F%%")
plt.show()
```



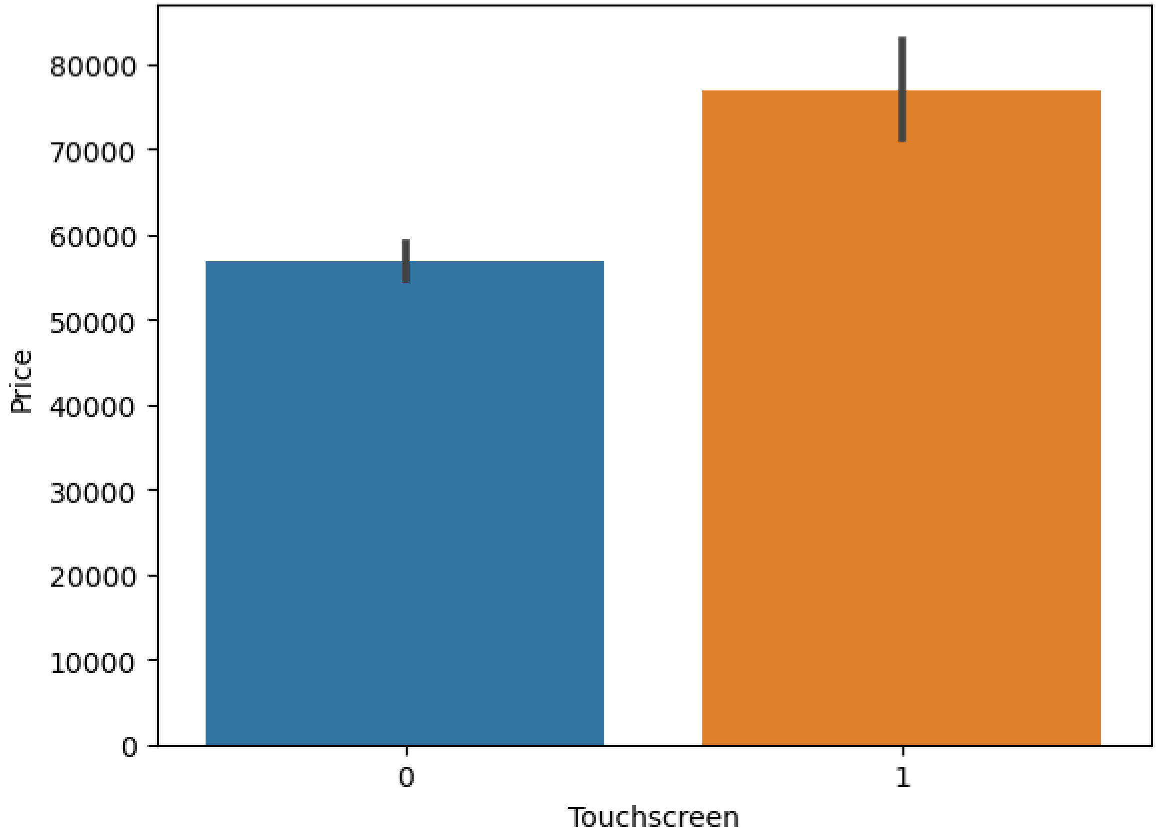
touchscreen laptops have capture about 15% of market.

In [25]:

```
sns.barplot(x=df["Touchscreen"],y=df["Price"])
```

Out[25]:

```
<AxesSubplot:xlabel='Touchscreen', ylabel='Price'>
```



touchscreen laptops varies with price range.

In [26]:

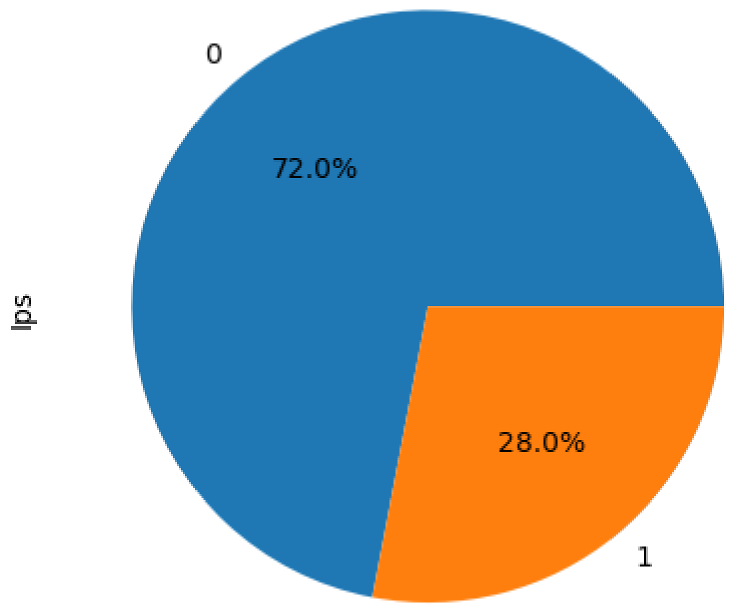
```
df["Ips"]=df["ScreenResolution"].apply(lambda x:1 if "IPS" in x else 0)
df["Ips"]
```

Out[26]:

```
0       1
1       0
2       0
3       1
4       1
       ..
1298    1
1299    1
1300    0
1301    0
1302    0
Name: Ips, Length: 1303, dtype: int64
```

In [27]:

```
df["Ips"].value_counts().plot(kind="pie",autopct="%0.1F%%")
plt.show()
```

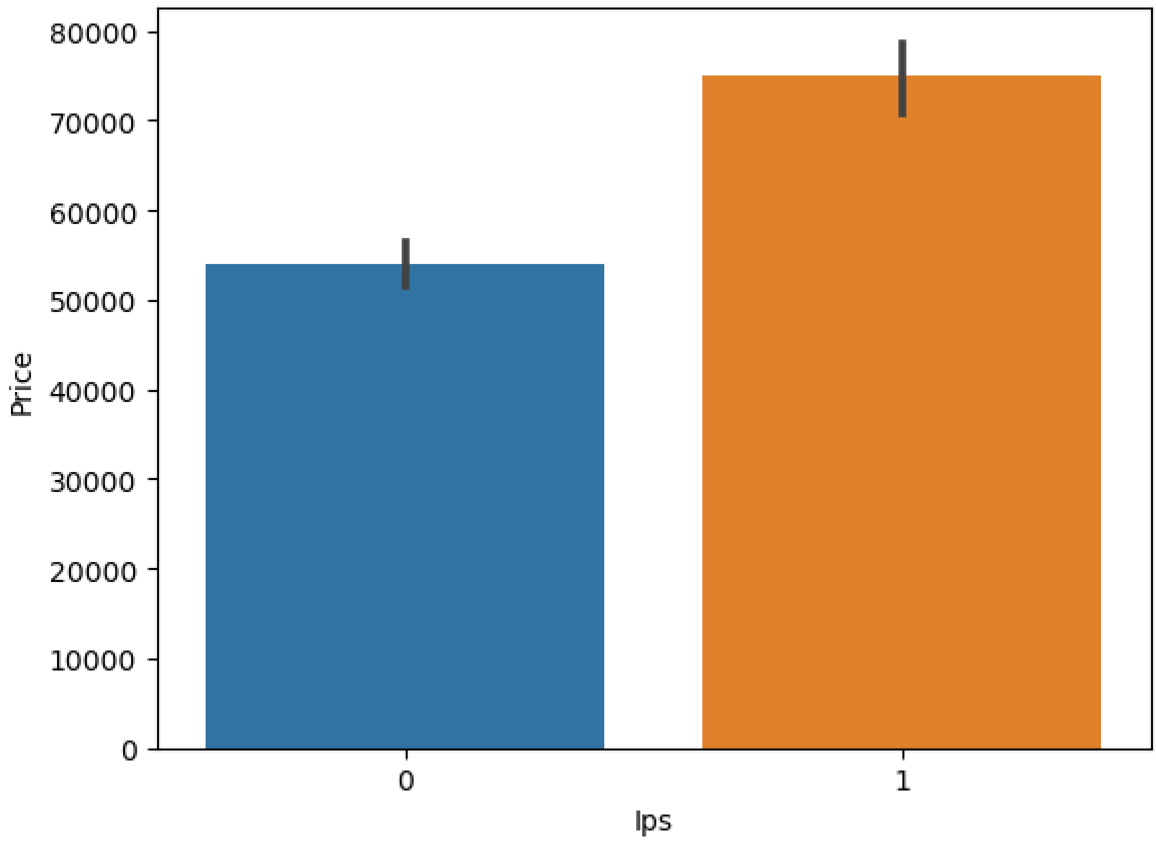


In [28]:

```
sns.barplot(x=df["Ips"],y=df["Price"])
```

Out[28]:

<AxesSubplot:xlabel='Ips', ylabel='Price'>



IPS Displays laptops having higher range.

In [29]:

```
new=df["ScreenResolution"].str.split("x",n=1,expand=True)
```

In [30]:

```
df["X_res"]=new[0]
df["Y_res"]=new[1]
```

In [31]:

```
df.head()
```

Out[31]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys	\
0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	
2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	
3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	
4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	

as we see we found correct y resolution but x resolution we have to do apply some regular expressions.

In [32]:

```
df["X_res"]=df["X_res"].str.replace(",","").str.findall(r'(\d+\.?\d+)').apply(lambda x:x[0]
```

In [33]:

```
df.head()
```

Out[33]:

	Company	TypeName	Inches	ScreenResolution	Cpu	Ram	Memory	Gpu	OpSys
0	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS
1	Apple	Ultrabook	13.3	1440x900	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS
2	HP	Notebook	15.6	Full HD 1920x1080	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS
3	Apple	Ultrabook	15.4	IPS Panel Retina Display 2880x1800	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS
4	Apple	Ultrabook	13.3	IPS Panel Retina Display 2560x1600	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS

In [34]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1303 entries, 0 to 1302
Data columns (total 15 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   Company           1303 non-null   object 
 1   TypeName          1303 non-null   object 
 2   Inches            1303 non-null   float64
 3   ScreenResolution  1303 non-null   object 
 4   Cpu               1303 non-null   object 
 5   Ram               1303 non-null   int32  
 6   Memory            1303 non-null   object 
 7   Gpu               1303 non-null   object 
 8   OpSys             1303 non-null   object 
 9   Weight            1303 non-null   float32
 10  Price             1303 non-null   float64
 11  Touchscreen       1303 non-null   int64  
 12  Ips               1303 non-null   int64  
 13  X_res             1303 non-null   object 
 14  Y_res             1303 non-null   object 
dtypes: float32(1), float64(2), int32(1), int64(2), object(9)
memory usage: 142.6+ KB
```

In [35]:

```
df["X_res"]=df["X_res"].astype("int")
df["Y_res"]=df["Y_res"].astype("int")
```

In [36]:

```
df.corr()["Price"]
```

Out[36]:

```
Inches         0.068197
Ram            0.743007
Weight         0.210370
Price          1.000000
Touchscreen    0.191226
Ips            0.252208
X_res          0.556529
Y_res          0.552809
Name: Price, dtype: float64
```

In [37]:

```
df["ppi"]=(((df["X_res"]**2+df["Y_res"]**2))**0.5/df["Inches"]).astype("float")
```

In [38]:

```
df.corr()["Price"]
```

Out[38]:

```
Inches         0.068197
Ram            0.743007
Weight         0.210370
Price          1.000000
Touchscreen    0.191226
Ips            0.252208
X_res          0.556529
Y_res          0.552809
ppi            0.473487
Name: Price, dtype: float64
```

In [39]:

```
df.drop(columns=["ScreenResolution"],inplace=True)
```

In [40]:

```
df.drop(columns=["Inches","X_res","Y_res"],inplace=True)
```

In [41]:

```
df.head()
```

Out[41]:

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touch
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	
2	HP	Notebook	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	
4	Apple	Ultrabook	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	

PPI stands for pixels per inches

PPI is highly corelated with price.

In [42]:

```
df["Cpu"].value_counts()
```

Out[42]:

```
Intel Core i5 7200U 2.5GHz       190
Intel Core i7 7700HQ 2.8GHz      146
Intel Core i7 7500U 2.7GHz       134
Intel Core i7 8550U 1.8GHz        73
Intel Core i5 8250U 1.6GHz        72
                                ... 
Intel Core M M3-6Y30 0.9GHz        1
AMD A9-Series 9420 2.9GHz          1
Intel Core i3 6006U 2.2GHz         1
AMD A6-Series 7310 2GHz            1
Intel Xeon E3-1535M v6 3.1GHz      1
Name: Cpu, Length: 118, dtype: int64
```

cpu have 118 diffrent categories and i5,i7 Intel Core are Some of the famous.

In [43]:

```
df["Cpu Name"]=df["Cpu"].apply(lambda x:" ".join(x.split()[0:3]))
```

In [44]:

```
df.head()
```

Out[44]:

	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touch
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	
2	HP	Notebook	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	
4	Apple	Ultrabook	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	

In [45]:

```
def fetch_processor(text):
    if text == 'Intel Core i7' or text == 'Intel Core i5' or text == 'Intel Core i3':
        return text
    else:
        if text.split()[0] == 'Intel':
            return 'Other Intel Processor'
        else:
            return 'AMD Processor'
```

In [46]:

```
df['Cpu brand'] = df['Cpu Name'].apply(fetch_processor)
```

In [47]:

```
df.head()
```

Out[47]:

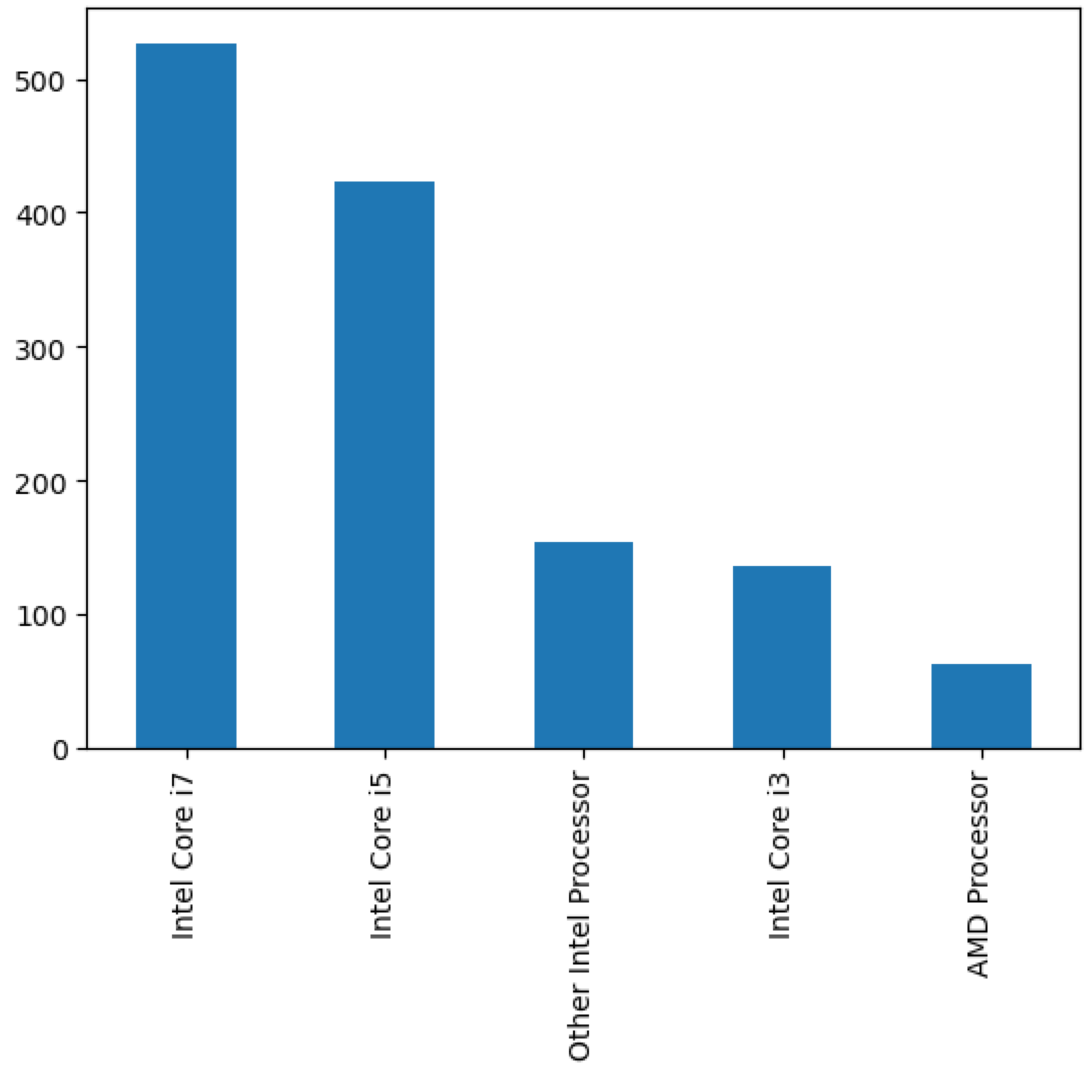
	Company	TypeName	Cpu	Ram	Memory	Gpu	OpSys	Weight	Price	Touch
0	Apple	Ultrabook	Intel Core i5 2.3GHz	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	
1	Apple	Ultrabook	Intel Core i5 1.8GHz	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	
2	HP	Notebook	Intel Core i5 7200U 2.5GHz	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	
3	Apple	Ultrabook	Intel Core i7 2.7GHz	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	
4	Apple	Ultrabook	Intel Core i5 3.1GHz	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	

In [48]:

```
df['Cpu brand'].value_counts().plot(kind='bar')
```

Out[48]:

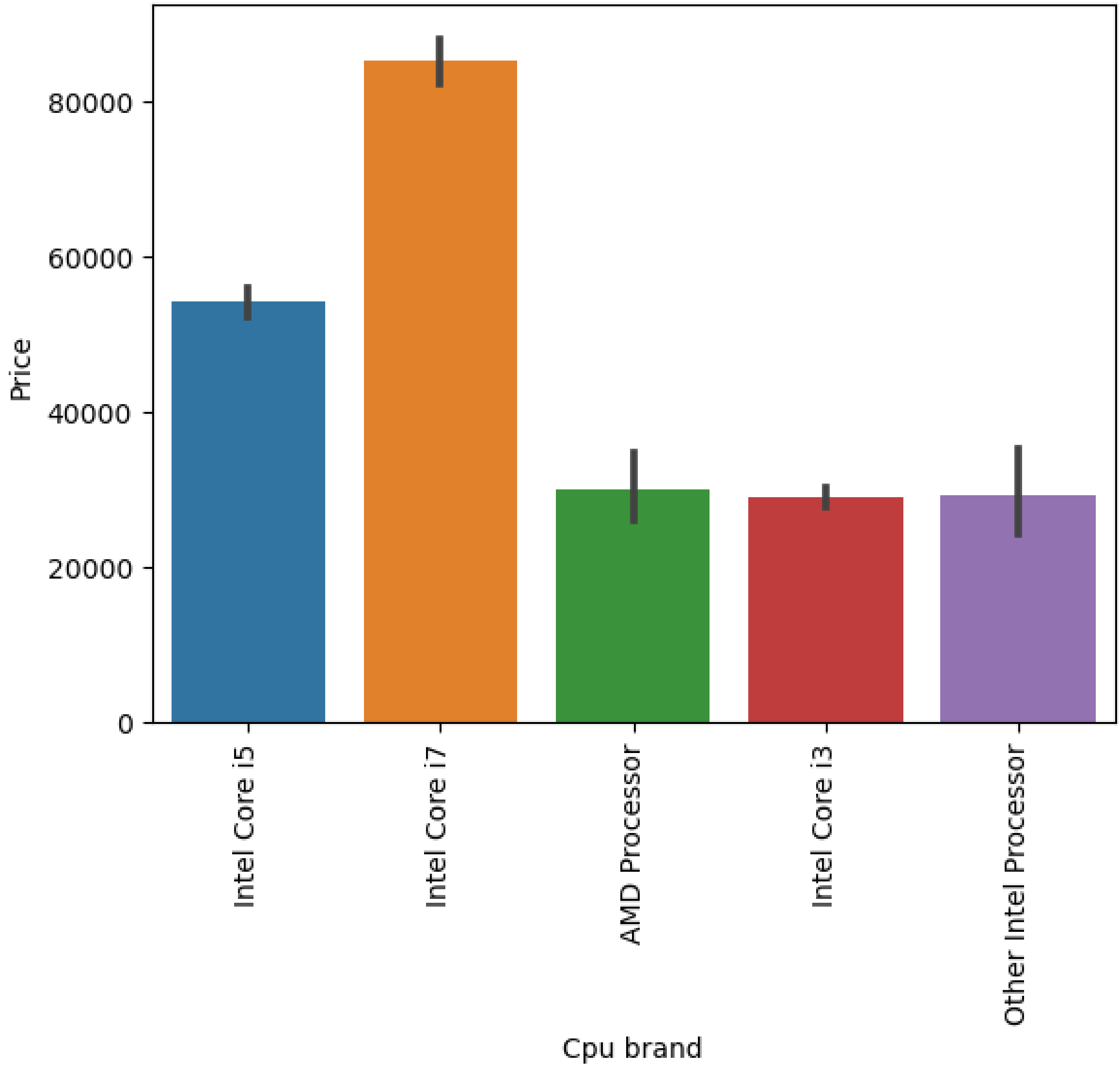
```
<AxesSubplot:>
```



intel core i7 generation is most widely used.

In [49]:

```
sns.barplot(x=df['Cpu brand'],y=df['Price'])
plt.xticks(rotation='vertical')
plt.show()
```



As with huge demand i7 processor is ranging higher price.

AMD processor,i3 processor and execpt i5 other intel having same price range.

we can say that price is varies along with processores.

In [50]:

```
df.drop(columns=["Cpu","Cpu Name"],inplace=True)
```

deleting unwanted columns as we have cpu brand for specifications.

In [51]:

```
df.head()
```

Out[51]:

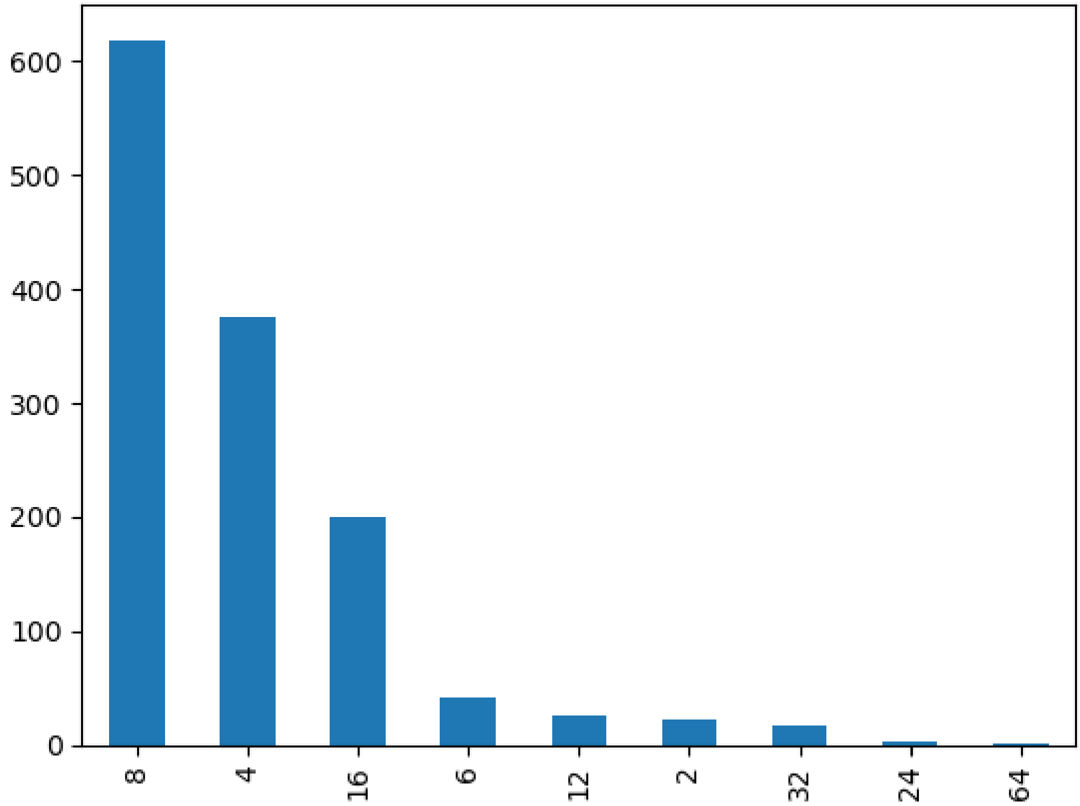
	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen
0	Apple	Ultrabook	8	128GB SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0
1	Apple	Ultrabook	8	128GB Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0
2	HP	Notebook	8	256GB SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	0
3	Apple	Ultrabook	16	512GB SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0
4	Apple	Ultrabook	8	256GB SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0

In [52]:

```
df["Ram"].value_counts().plot(kind="bar")
```

Out[52]:

<AxesSubplot:>



8gb Ram laptops are standerd size and those are most selling laptops as well.

surprisingly 4gb Ram laptops still ahead from 16gb Ram laptops.

64,24,32Gb laptops is vary rare in market.

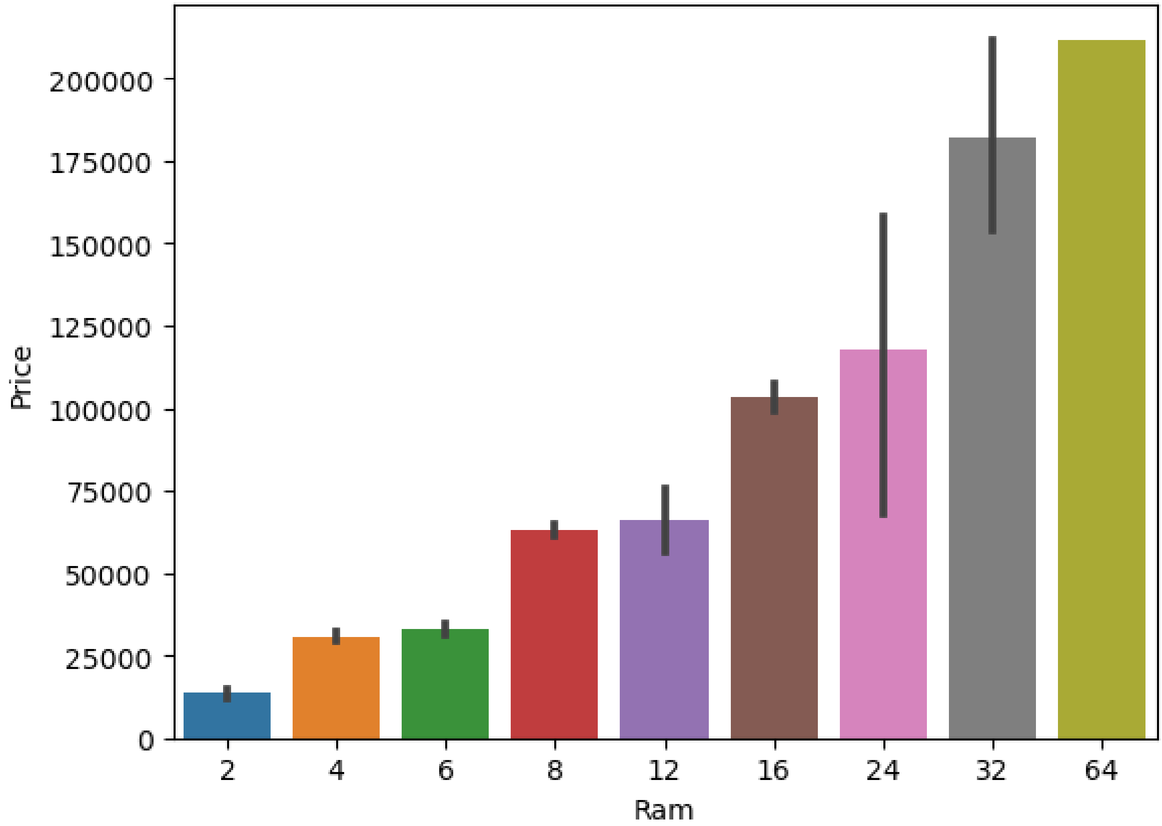
2gb laptops are outdated Now.

In [53]:

```
sns.barplot(x=df["Ram"],y=df["Price"])
```

Out[53]:

```
<AxesSubplot:xlabel='Ram', ylabel='Price'>
```



highly correlation between Ram and Price.

even though 12gb ram laptops are in godd price range but still its under rated in market.

In [54]:

```
df["Memory"].value_counts()
```

Out[54]:

```
256GB SSD                        412
1TB HDD                          223
500GB HDD                        132
512GB SSD                        118
128GB SSD +  1TB HDD              94
128GB SSD                         76
256GB SSD +  1TB HDD              73
32GB Flash Storage                38
2TB HDD                           16
64GB Flash Storage                15
512GB SSD +  1TB HDD              14
1TB SSD                           14
256GB SSD +  2TB HDD              10
1.0TB Hybrid                       9
256GB Flash Storage                8
16GB Flash Storage                 7
32GB SSD                           6
180GB SSD                          5
128GB Flash Storage                4
512GB SSD +  2TB HDD               3
16GB SSD                           3
512GB Flash Storage                2
1TB SSD +  1TB HDD                 2
256GB SSD +  500GB HDD             2
128GB SSD +  2TB HDD               2
256GB SSD +  256GB SSD             2
512GB SSD +  256GB SSD             1
512GB SSD +  512GB SSD             1
64GB Flash Storage +  1TB HDD      1
1TB HDD +  1TB HDD                 1
32GB HDD                           1
64GB SSD                           1
128GB HDD                          1
240GB SSD                          1
8GB SSD                            1
508GB Hybrid                       1
1.0TB HDD                          1
512GB SSD +  1.0TB Hybrid          1
256GB SSD +  1.0TB Hybrid          1
Name: Memory, dtype: int64
```

In [55]:

```
df["Memory"]
```

Out[55]:

```
0                 128GB SSD
1       128GB Flash Storage
2                 256GB SSD
3                 512GB SSD
4                 256GB SSD
               ...
1298              128GB SSD
1299              512GB SSD
1300     64GB Flash Storage
1301                1TB HDD
1302              500GB HDD
Name: Memory, Length: 1303, dtype: object
```

In [56]:

```
df['Memory'] = df['Memory'].astype(str)
```

In [57]:

```
df['Memory']
```

Out[57]:

```
0                 128GB SSD
1       128GB Flash Storage
2                 256GB SSD
3                 512GB SSD
4                 256GB SSD
               ...
1298              128GB SSD
1299              512GB SSD
1300     64GB Flash Storage
1301                1TB HDD
1302              500GB HDD
Name: Memory, Length: 1303, dtype: object
```

In [58]:

```
df["Memory"] = df["Memory"].str.replace('GB', '')
```

In [59]:

```
df["Memory"] = df["Memory"].str.replace('TB', '000')
```

In [60]:

```
new = df["Memory"].str.split(n=1,expand = True)
```

In [61]:

```
new
```

Out[61]:

	0	1
0	128	SSD
1	128	Flash Storage
2	256	SSD
3	512	SSD
4	256	SSD
...	...	...
1298	128	SSD
1299	512	SSD
1300	64	Flash Storage
1301	1000	HDD
1302	500	HDD

1303 rows × 2 columns

In [62]:

```
df["first"]= new[0]
```

In [63]:

```
df["first"]=df["first"].str.strip()
#removing unwanted space
```

In [64]:

```
df["first"]
```

Out[64]:

```
0        128
1        128
2        256
3        512
4        256
        ...
1298     128
1299     512
1300      64
1301    1000
1302     500
Name: first, Length: 1303, dtype: object
```

In [65]:

```
df['first'].value_counts()
```

Out[65]:

```
256       508
1000      240
128       177
512       140
500       132
32         45
64         17
2000       16
1.0000     10
16         10
180         5
240         1
8           1
508         1
Name: first, dtype: int64
```

In [66]:

```
df["second"]= new[1]
```

In [67]:

```
df["second"]=df["second"].str.strip()
df["second"]
```

Out[67]:

```
0                 SSD
1       Flash Storage
2                 SSD
3                 SSD
4                 SSD
            ...
1298              SSD
1299              SSD
1300    Flash Storage
1301              HDD
1302              HDD
Name: second, Length: 1303, dtype: object
```

In [68]:

```
df["Layer1HDD"] = df["first"].apply(lambda x: 1 if "HDD" in x else 0)
df["Layer1SSD"] = df["first"].apply(lambda x: 1 if "SSD" in x else 0)
df["Layer1Hybrid"] = df["first"].apply(lambda x: 1 if "Hybrid" in x else 0)
df["Layer1Flash_Storage"] = df["first"].apply(lambda x: 1 if "Flash Storage" in x else 0)
```

In [69]:

```
df["Layer1Hybrid"].value_counts()
```

Out[69]:

```
0    1303
Name: Layer1Hybrid, dtype: int64
```

In [70]:

```
df["Layer1HDD"].value_counts()
```

Out[70]:

```
0    1303
Name: Layer1HDD, dtype: int64
```

In [71]:

```
df["Layer1SSD"].value_counts()
```

Out[71]:

```
0    1303
Name: Layer1SSD, dtype: int64
```

In [72]:

```
df["Layer1Flash_Storage"].value_counts()
```

Out[72]:

```
0    1303
Name: Layer1Flash_Storage, dtype: int64
```

In [73]:

```
df["second"].isnull().sum()
```

Out[73]:

```
0
```

In [74]:

```
df["Layer2HDD"] = df["second"].apply(lambda x: 1 if "HDD" in x else 0)
df["Layer2SSD"] = df["second"].apply(lambda x: 1 if "SSD" in x else 0)
df["Layer2Hybrid"] = df["second"].apply(lambda x: 1 if "Hybrid" in x else 0)
df["Layer2Flash_Storage"] = df["second"].apply(lambda x: 1 if "Flash Storage" in x else 0)
```

In [75]:

```
df["Layer2HDD"].value_counts()
```

Out[75]:

```
0    727
1    576
Name: Layer2HDD, dtype: int64
```

In [76]:

```
df["Layer2SSD"].value_counts()
#as we see SSD is booming the market.
```

Out[76]:

```
1    843
0    460
Name: Layer2SSD, dtype: int64
```

In [77]:

```
df["Layer2Hybrid"].value_counts()
```

Out[77]:

```
0    1291
1      12
Name: Layer2Hybrid, dtype: int64
```

In [78]:

```
df["Layer2Flash_Storage"].value_counts()
```

Out[78]:

```
0    1228
1      75
Name: Layer2Flash_Storage, dtype: int64
```

In [79]:

```
df["second"]
```

Out[79]:

```
0                 SSD
1       Flash Storage
2                 SSD
3                 SSD
4                 SSD
            ...
1298              SSD
1299              SSD
1300    Flash Storage
1301              HDD
1302              HDD
Name: second, Length: 1303, dtype: object
```

In [80]:

```
df['first'] = df['first'].str.replace(r'\D', '')
df['second'] = df['first'].str.replace(r'\D', '')
```

In [81]:

```
df["first"] = df["first"].astype(int)
df["second"] = df["second"].astype(int)
```

In [82]:

```
df["HDD"]=(df["first"]*df["Layer1HDD"]+df["second"]*df["Layer2HDD"])
df["SSD"]=(df["first"]*df["Layer1SSD"]+df["second"]*df["Layer2SSD"])
df["Hybrid"]=(df["first"]*df["Layer1Hybrid"]+df["second"]*df["Layer2Hybrid"])
df["Flash_Storage"]=(df["first"]*df["Layer1Flash_Storage"]+df["second"]*df["Layer2Flash_Sto
```

In [83]:

```
df["second"]
```

Out[83]:

```
0        128
1        128
2        256
3        512
4        256
        ...
1298     128
1299     512
1300      64
1301    1000
1302     500
Name: second, Length: 1303, dtype: int32
```

In [84]:

```
df.sample(5)
```

Out[84]:

	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreer
179	HP	2 in 1 Convertible	8	256 SSD	Intel UHD Graphics 620	Windows 10	1.29	79866.7200	‘
136	Lenovo	Notebook	4	1000 HDD	Intel HD Graphics 500	No OS	1.90	13445.7408	(
481	Dell	Notebook	4	1000 HDD	Intel HD Graphics 620	Windows 10	2.18	31254.0480	(
134	HP	Notebook	8	1000 HDD	Intel HD Graphics 620	Windows 10	2.05	31861.4400	(
560	Acer	2 in 1 Convertible	4	32 Flash Storage	Intel HD Graphics 500	Windows 10	1.25	18594.7200	‘

5 rows × 26 columns

In [85]:

```
df.drop(columns=['first', 'second', 'Layer1HDD', 'Layer1SSD', 'Layer1Hybrid',
       'Layer1Flash_Storage', 'Layer2HDD', 'Layer2SSD', 'Layer2Hybrid',
       'Layer2Flash_Storage'],inplace=True)
```

In [86]:

```
df.head()
```

Out[86]:

	Company	TypeName	Ram	Memory	Gpu	OpSys	Weight	Price	Touchscreen
0	Apple	Ultrabook	8	128 SSD	Intel Iris Plus Graphics 640	macOS	1.37	71378.6832	0
1	Apple	Ultrabook	8	128 Flash Storage	Intel HD Graphics 6000	macOS	1.34	47895.5232	0
2	HP	Notebook	8	256 SSD	Intel HD Graphics 620	No OS	1.86	30636.0000	0
3	Apple	Ultrabook	16	512 SSD	AMD Radeon Pro 455	macOS	1.83	135195.3360	0
4	Apple	Ultrabook	8	256 SSD	Intel Iris Plus Graphics 650	macOS	1.37	96095.8080	0

as we have functions of meomery so there no use of memory column.

In [87]:

```
df.drop(columns=["Memory"],inplace=True)
```

In [88]:

```
df.corr()['Price']
```

Out[88]:

```
Ram             0.743007
Weight          0.210370
Price           1.000000
Touchscreen     0.191226
Ips             0.252208
ppi             0.473487
HDD            -0.265334
SSD             0.676202
Hybrid         -0.037971
Flash_Storage  -0.040511
Name: Price, dtype: float64
```

SSD and HDD are still have huge market capture but HDD is negatively co-related to price.

hybrid and flash_storage is still low market capture as with negative co-relation so we deleting this column.

In [89]:

```
df.drop(columns=['Hybrid','Flash_Storage'],inplace=True)
```

GPU (graphical processing unit)

it shows which graphic card is having in laptop.

In [90]:

```
df["Gpu"].value_counts()
```

Out[90]:

```
Intel HD Graphics 620      281
Intel HD Graphics 520      185
Intel UHD Graphics 620      68
Nvidia GeForce GTX 1050     66
Nvidia GeForce GTX 1060     48
                          ...
AMD Radeon R5 520            1
AMD Radeon R7                1
Intel HD Graphics 540        1
AMD Radeon 540               1
ARM Mali T860 MP4            1
Name: Gpu, Length: 110, dtype: int64
```

In [91]:

```
df["Gpu brand"]=df["Gpu"].apply(lambda x:x.split()[0])
```

In [92]:

```
df["Gpu brand"]
```

Out[92]:

```
0       Intel
1       Intel
2       Intel
3         AMD
4       Intel
        ...
1298    Intel
1299    Intel
1300    Intel
1301      AMD
1302    Intel
Name: Gpu brand, Length: 1303, dtype: object
```

here gpu column contains lots of mixed info hence we are going for only GPU brands.

In [93]:

```
df["Gpu brand"].value_counts()
```

Out[93]:

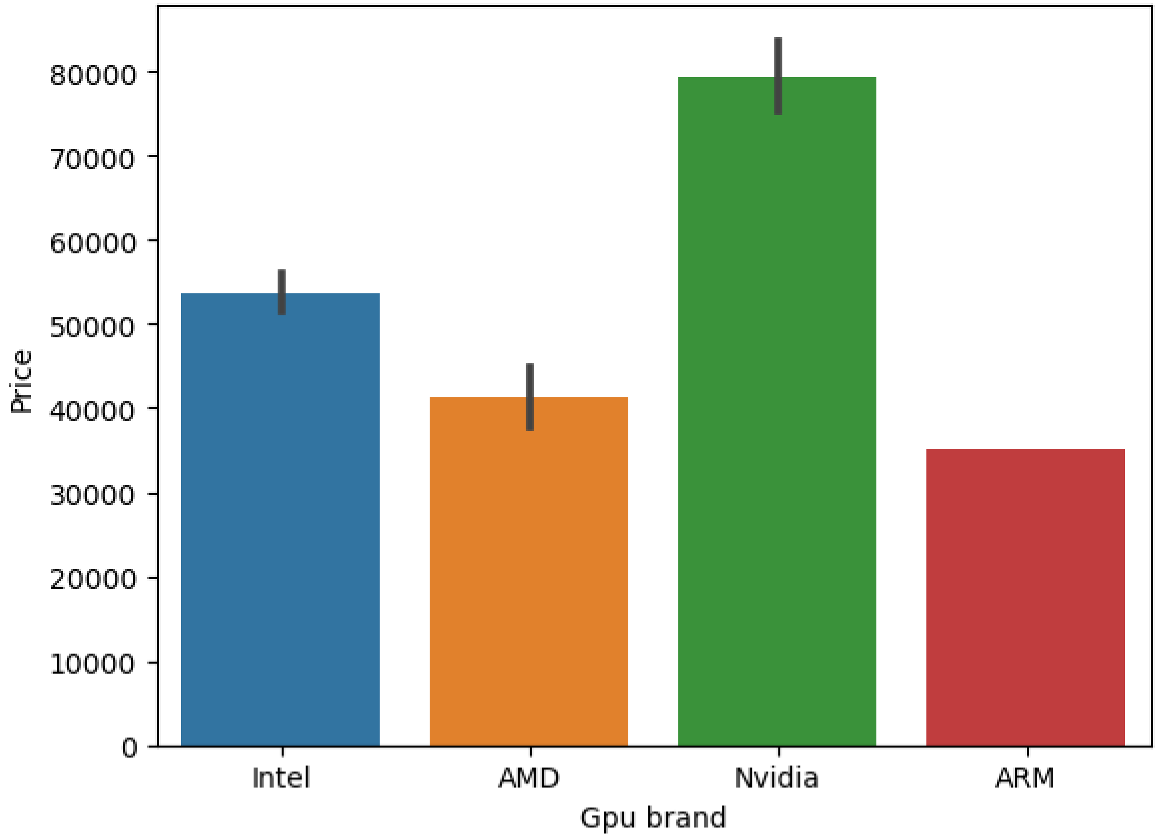
```
Intel     722
Nvidia    400
AMD       180
ARM         1
Name: Gpu brand, dtype: int64
```

In [94]:

```
sns.barplot(x=df["Gpu brand"],y=df["Price"])
```

Out[94]:

```
<AxesSubplot:xlabel='Gpu brand', ylabel='Price'>
```



Nvidia is expensive grahic cards and its mostly used for gaming laptops.

in reacent days intel introduce new graphic cards which are quite expensive thats its surpasses AMD.

In [95]:

```
df.drop(columns=["Gpu"],inplace=True)
```

Opsys(opreating system)

In [96]:

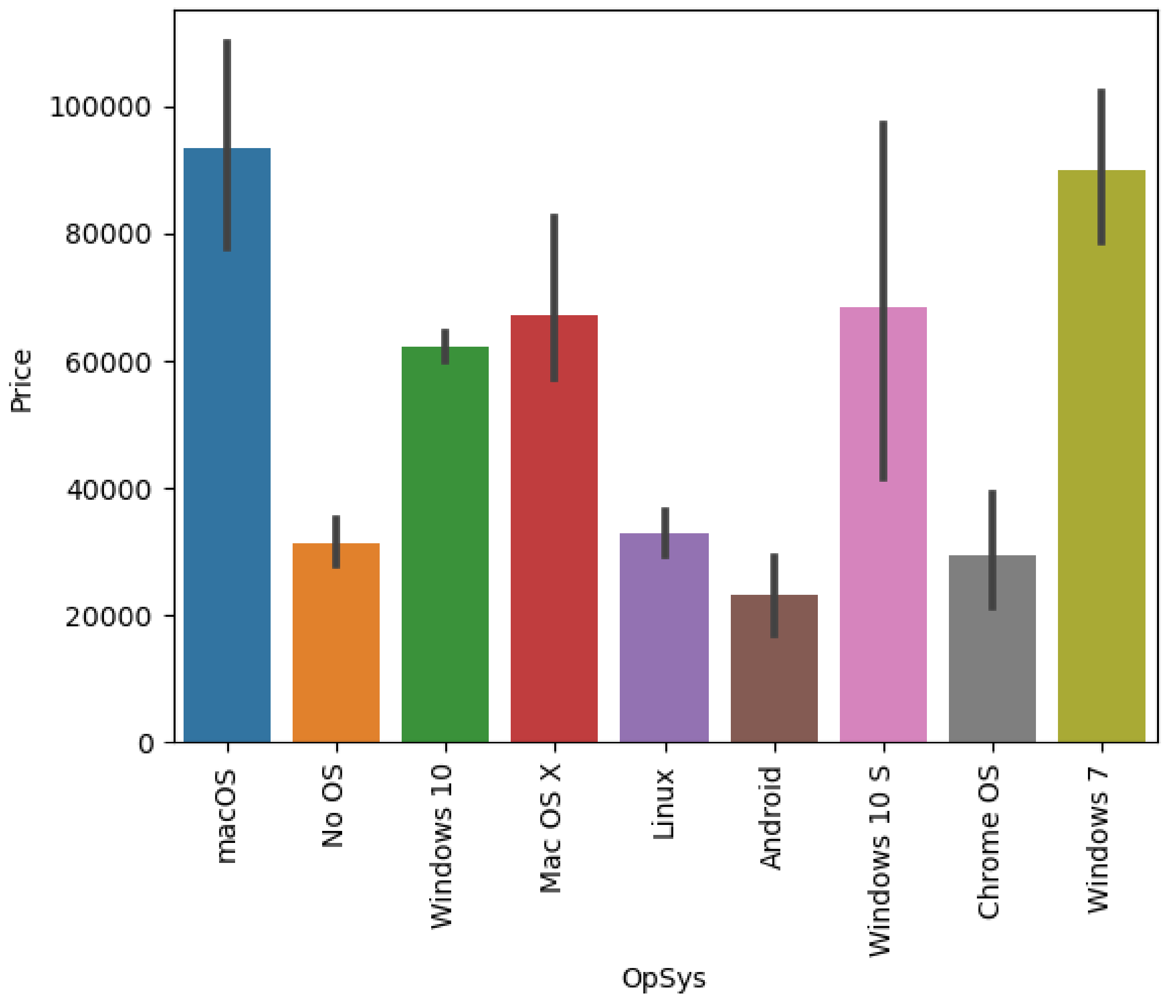
```
df["OpSys"].value_counts()
```

Out[96]:

```
Windows 10      1072
No OS             66
Linux             62
Windows 7         45
Chrome OS         27
macOS             13
Mac OS X           8
Windows 10 S       8
Android            2
Name: OpSys, dtype: int64
```

In [97]:

```
sns.barplot(x=df['OpSys'],y=df['Price'])
plt.xticks(rotation='vertical')
plt.show()
```



since we have too much categories now in os hence we club into a groups.

In [98]:

```
def cat_os(inp):
    if inp == 'Windows 10' or inp == 'Windows 7' or inp == 'Windows 10 S':
        return 'Windows'
    elif inp == 'macOS' or inp == 'Mac OS X':
        return 'Mac'
    else:
        return 'Others/No OS/Linux'
```

In [99]:

```
df['os'] = df['OpSys'].apply(cat_os)
```

In [100]:

```
df.head()
```

Out[100]:

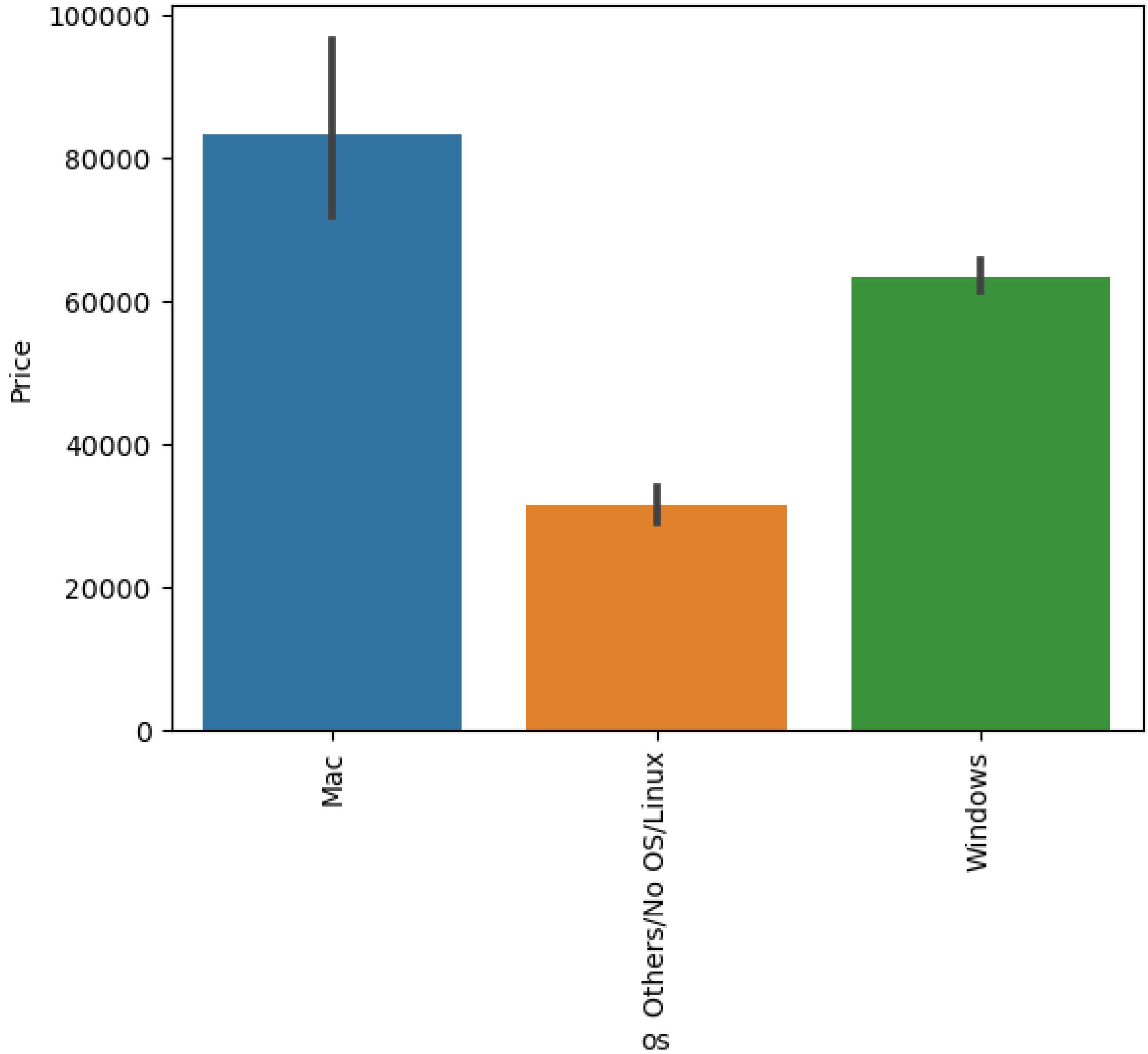
	Company	TypeName	Ram	OpSys	Weight	Price	Touchscreen	Ips	ppi	C bra
0	Apple	Ultrabook	8	macOS	1.37	71378.6832	0	1	226.983005	I C
1	Apple	Ultrabook	8	macOS	1.34	47895.5232	0	0	127.677940	I C
2	HP	Notebook	8	No OS	1.86	30636.0000	0	0	141.211998	I C
3	Apple	Ultrabook	16	macOS	1.83	135195.3360	0	1	220.534624	I C
4	Apple	Ultrabook	8	macOS	1.37	96095.8080	0	1	226.983005	I C

In [101]:

```
df.drop(columns=['OpSys'],inplace=True)
```

In [102]:

```
sns.barplot(x=df['os'],y=df['Price'])
plt.xticks(rotation='vertical')
plt.show()
```



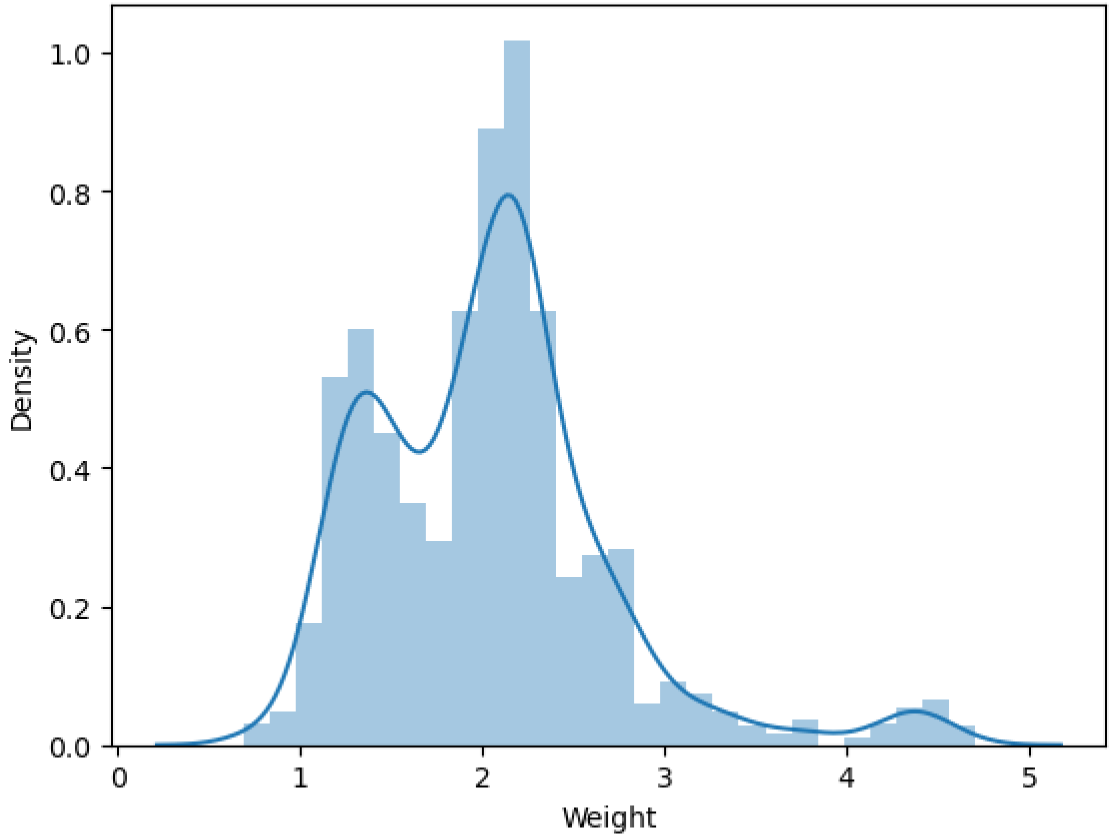
Mac opereating systems are one of expensive ones.

In [103]:

```
sns.distplot(df['Weight'])
```

Out[103]:

<AxesSubplot:xlabel='Weight', ylabel='Density'>

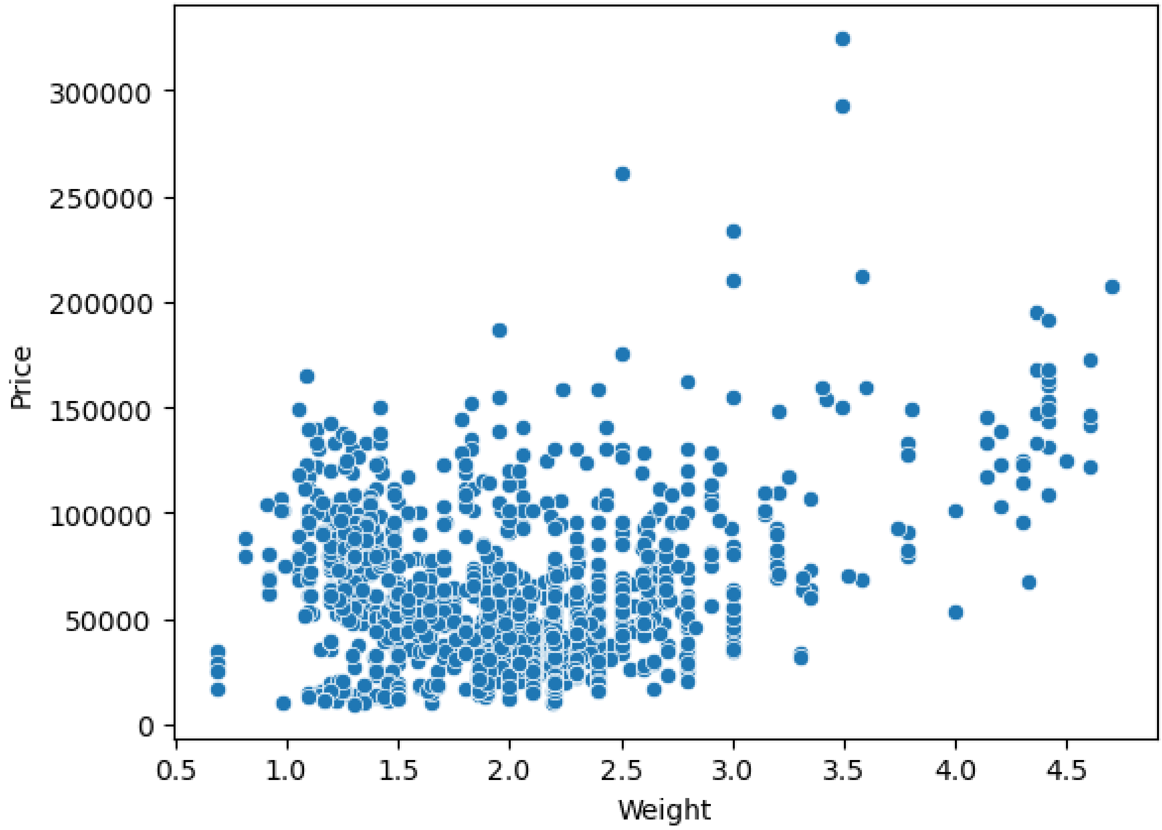


In [104]:

```
sns.scatterplot(x=df['Weight'],y=df['Price'])
```

Out[104]:

```
<AxesSubplot:xlabel='Weight', ylabel='Price'>
```



distriburion is slightly linear.

In [105]:

```
df.corr()['Price']
```

Out[105]:

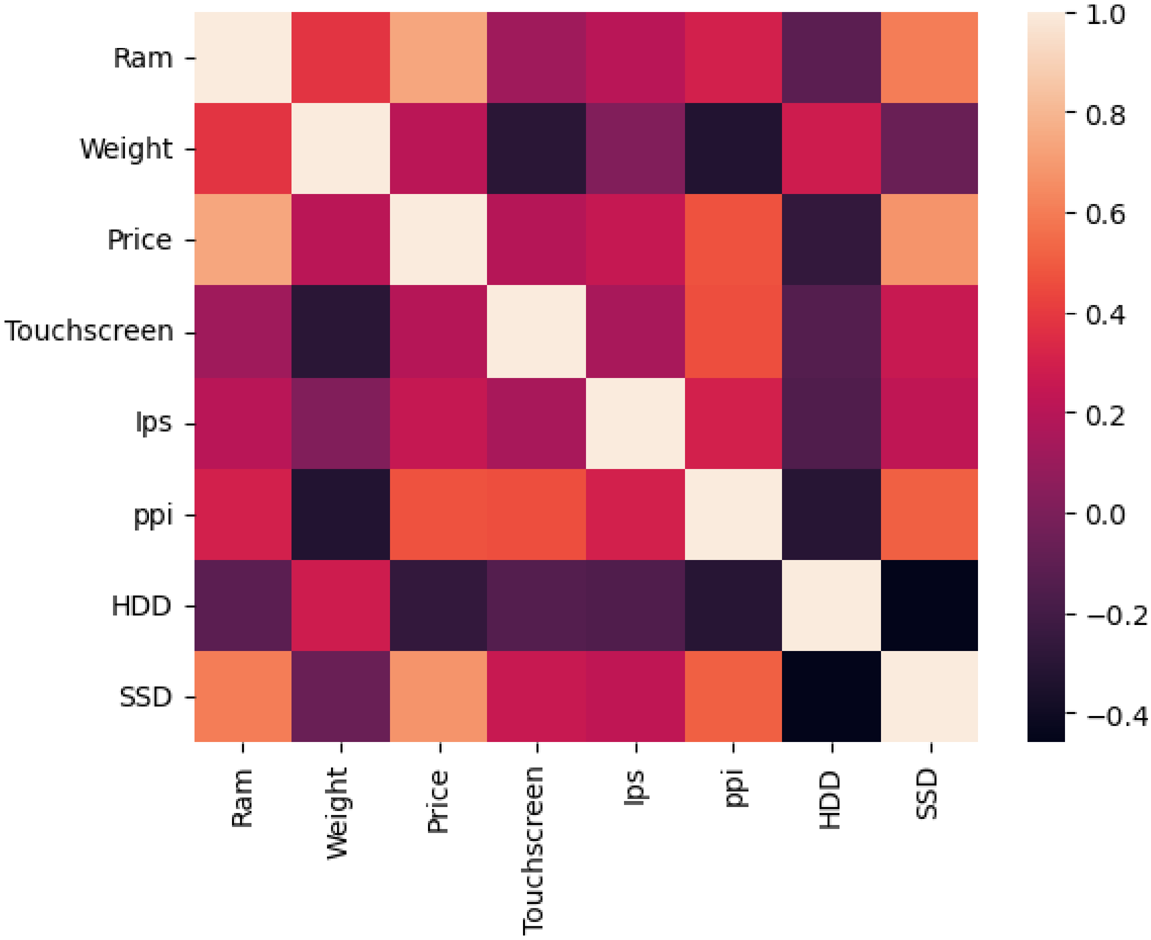
```
Ram            0.743007
Weight         0.210370
Price          1.000000
Touchscreen    0.191226
Ips            0.252208
ppi            0.473487
HDD           -0.265334
SSD            0.676202
Name: Price, dtype: float64
```

In [106]:

```
sns.heatmap(df.corr())
```

Out[106]:

<AxesSubplot:>

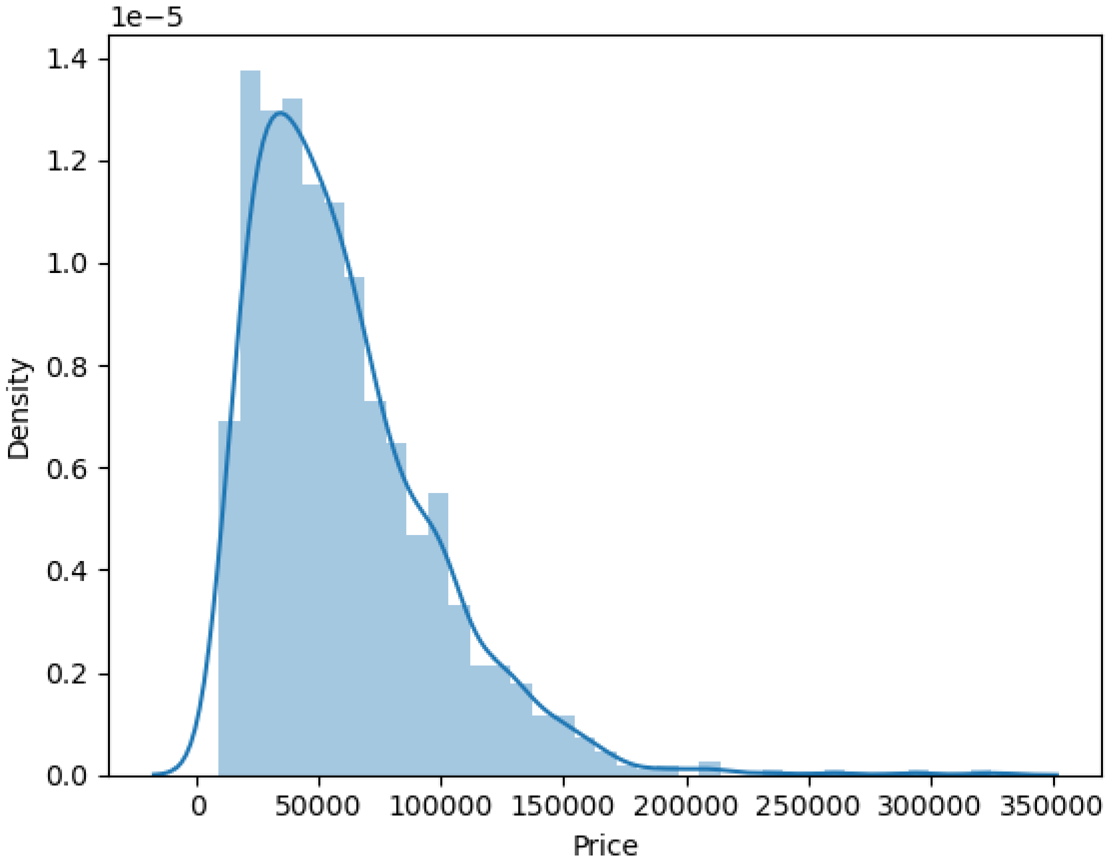


In [107]:

```
sns.distplot(df['Price'])
```

Out[107]:

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```

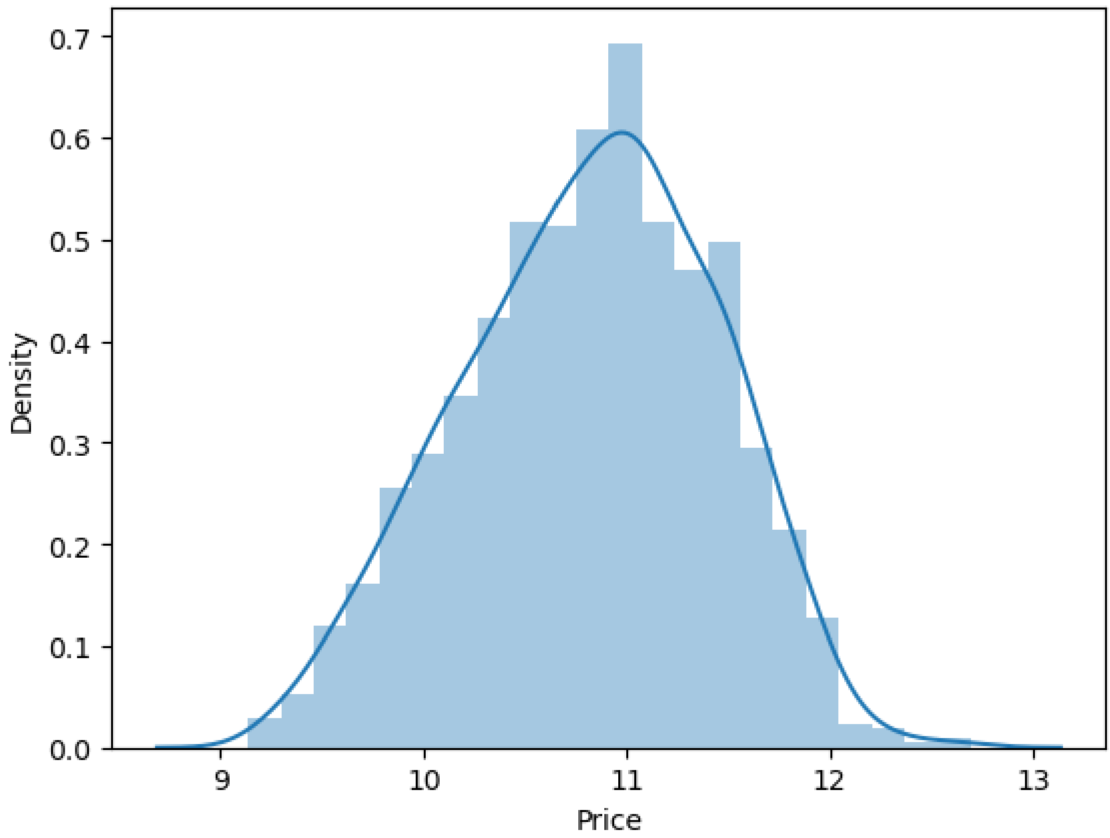


In [108]:

```
sns.distplot(np.log(df['Price']))
```

Out[108]:

```
<AxesSubplot:xlabel='Price', ylabel='Density'>
```



In [109]:

```
X = df.drop(columns=['Price'])
y = np.log(df['Price'])
```

In [110]:

```
X
#this are independent variables which 12 columns.
```

Out[110]:

	Company	TypeName	Ram	Weight	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD
0	Apple	Ultrabook	8	1.37	0	1	226.983005	Intel Core i5	0	128
1	Apple	Ultrabook	8	1.34	0	0	127.677940	Intel Core i5	0	0
2	HP	Notebook	8	1.86	0	0	141.211998	Intel Core i5	0	256
3	Apple	Ultrabook	16	1.83	0	1	220.534624	Intel Core i7	0	512
4	Apple	Ultrabook	8	1.37	0	1	226.983005	Intel Core i5	0	256
...	...	...	...	...	...	...	...	...	...	...
1298	Lenovo	2 in 1 Convertible	4	1.80	1	1	157.350512	Intel Core i7	0	128
1299	Lenovo	2 in 1 Convertible	16	1.30	1	1	276.053530	Intel Core i7	0	512
1300	Lenovo	Notebook	2	1.50	0	0	111.935204	Other Intel Processor	0	0
1301	HP	Notebook	6	2.19	0	0	100.454670	Intel Core i7	1000	0
1302	Asus	Notebook	4	2.20	0	0	100.454670	Other Intel Processor	500	0

1303 rows × 12 columns

In [111]:

```
y
```

Out[111]:

```
0       11.175755
1       10.776777
2       10.329931
3       11.814476
4       11.473101
          ...
1298    10.433899
1299    11.288115
1300     9.409283
1301    10.614129
1302     9.886358
Name: Price, Length: 1303, dtype: float64
```

Train-test-split

In [112]:

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.15,random_state=123)
```

In [113]:

```
X_train
```

Out[113]:

	Company	TypeName	Ram	Weight	Touchscreen	Ips	ppi	Cpu brand	HDD	SSD
69	Asus	Gaming	12	3.00	0	0	127.335675	Intel Core i7	1000	0
1278	Dell	Notebook	2	2.20	0	0	100.454670	Other Intel Processor	500	0
478	Dell	Notebook	8	2.20	0	0	141.211998	Intel Core i5	1000	0
184	Xiaomi	Notebook	8	1.95	0	1	141.211998	Intel Core i5	0	256
922	HP	Ultrabook	8	1.39	1	0	276.053530	Intel Core i7	0	256
...	...	...	...	...	...	...	...	...	...	...
1238	MSI	Gaming	8	2.30	0	0	141.211998	Intel Core i7	128	128
1147	Dell	Notebook	8	2.18	0	0	141.211998	Intel Core i7	0	256
106	Lenovo	Notebook	4	1.85	0	0	141.211998	Intel Core i3	1000	0
1041	Vero	Notebook	2	1.45	0	0	111.935204	Other Intel Processor	0	0
1122	HP	Notebook	8	1.43	0	0	157.350512	Intel Core i5	0	256

1107 rows × 12 columns

In [114]:

```
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error
```

In [115]:

```
from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.neighbors import KNeighborsRegressor
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor,GradientBoostingRegressor,AdaBoostRegres
from sklearn.svm import SVR
```

In [116]:

```
import sys
!{sys.executable} -m pip install xgboost
```

```
Defaulting to user installation because normal site-packages is not writeabl
e
Requirement already satisfied: xgboost in c:\users\hp\appdata\roaming\python
\python39\site-packages (1.7.3)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site-pa
ckages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site-pa
ckages (from xgboost) (1.21.5)
```

In [140]:

```
from xgboost import XGBRegressor
```

Linear Regression

In [131]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = LinearRegression()

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8526942961347356
MAE 0.20451400133765388
RMSE 0.4522322427002014
MSE 0.06614340286466652
```

hyper parameter Tunning

Ridge Regression

In [130]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = Ridge(alpha=10)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8477234251713205
MAE 0.20879528428859737
RMSE 0.4569412262956773
MSE 0.06837542994911786
```

Lasso Regression

In [129]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = Lasso(alpha=0.001)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8490794469515934
MAE 0.20801757576114935
RMSE 0.4560894383354534
MSE 0.06776654724768563
```

KNN

In [121]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = KNeighborsRegressor(n_neighbors=5)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8552974239889848
MAE 0.19218436481485893
RMSE 0.4383883721255149
MSE 0.06497454293695236
```

In [122]:

```
from sklearn.model_selection import RandomizedSearchCV
```

Desicion Tree

In [123]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = DecisionTreeRegressor(max_depth=9)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8138158940301548
MAE 0.2149598043711364
RMSE 0.46363757868742306
MSE 0.08360063463275813
```

SVM

In [124]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = SVR(kernel='rbf',C=10000,epsilon=0.1)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.870913312883457
MAE 0.18706792440450393
RMSE 0.4325134962108164
MSE 0.05796267575778530
```

Random Forest

In [125]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = RandomForestRegressor(n_estimators=100,
                              random_state=3,
                              max_samples=0.5,
                              max_features=0.75,
                              max_depth=15)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8975403329325123
MAE 0.16747577694368812
RMSE 0.40923804435033667
MSE 0.04600657583784514
```

ExtraTrees

In [126]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = ExtraTreesRegressor(n_estimators=100,
                              random_state=3,
                              max_samples=None,
                              max_features=0.75,
                              max_depth=15)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.8779980095677018
MAE 0.17769136725515164
RMSE 0.42153453862661316
MSE 0.05478149583967034
```

Ada Boost

In [127]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = AdaBoostRegressor(n_estimators=15,learning_rate=1.0)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.805499437899004
MAE 0.24263972831228917
RMSE 0.49258474226501286
MSE 0.08733490081427797
```

Gradient Boost

In [128]:

```
step1 = ColumnTransformer(transformers=[
    ('col_tnf',OneHotEncoder(sparse=False,drop='first'),[0,1,7,10,11])
],remainder='passthrough')

step2 = GradientBoostingRegressor(n_estimators=500)

pipe = Pipeline([
    ('step1',step1),
    ('step2',step2)
])

pipe.fit(X_train,y_train)

y_pred = pipe.predict(X_test)

print('R2 score',r2_score(y_test,y_pred))
print('MAE',mean_absolute_error(y_test,y_pred))
print('RMSE',np.sqrt(mean_absolute_error(y_test,y_pred)))
print('MSE',mean_squared_error(y_test,y_pred))
```

```
R2 score 0.9094125907471093
MAE 0.1471677735721633
RMSE 0.3836245215991325
MSE 0.04067567886007201
```

In [136]:

```
report ={"Regression Algorithms": ["LinearRegression","Ridge Regression"," lasso Regression
      "R2 Score": [0.852,0.847,0.849,0.855,0.813,0.870,0.897,0.877,0.805,0.909],"MAE":[0.20
```

In [137]:

```
report=pd.DataFrame(report)
```

In [138]:

```
report
```

Out[138]:

	Regression Algorithms	R2 Score	MAE	RMSE	MSE
0	LinearRegression	0.852	0.204	0.452	0.066
1	Ridge Regression	0.847	0.208	0.456	0.068
2	lasso Regression	0.849	0.208	0.456	0.067
3	KNN Regressor	0.855	0.192	0.438	0.064
4	Decision Tree Regressor	0.813	0.214	0.463	0.083
5	SVM	0.870	0.187	0.432	0.057
6	RandomForestRegressor	0.897	0.167	0.409	0.046
7	ExtraTreesRegressor	0.877	0.177	0.421	0.054
8	AdaBoostRegressor	0.805	0.242	0.491	0.087
9	GradientBoostingRegressor	0.909	0.147	0.383	0.040

Gradient Boost and Random Forest are best regression model for this dataset.

In [139]:

```
pip install xgboost
```

```
Defaulting to user installation because normal site-packages is not writeabl
eNote: you may need to restart the kernel to use updated packages.

Requirement already satisfied: xgboost in c:\users\hp\appdata\roaming\python
\python39\site-packages (1.7.3)
Requirement already satisfied: scipy in c:\programdata\anaconda3\lib\site-pa
ckages (from xgboost) (1.9.1)
Requirement already satisfied: numpy in c:\programdata\anaconda3\lib\site-pa
ckages (from xgboost) (1.21.5)
```

In [ ]:

```

```